MATERIAL (DATA) INTELLIGENCE

Towards a Circular Building Environment

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Abstract. The integration of repurposed material in new construction products generates resiliency strategies that diminish the dependency on raw resources and reduce the CO2 emissions produced by their extraction, transportation, and manufacturing. This research emphasizes the need to expand preliminary data collation from pre-demolition sites to inform early design decisions. Material (data) Intelligence investigates how the merging of artificial intelligence and data analysis could have a crucial impact on achieving widespread material reuse. The first step consists of automating the process of detecting materials and construction elements from pre-demolition sites through drone photography and computer vision. The second part of the research links the resulting database with a computational design tool that can be integrated into construction software. This paper strengthens the potential of circular material flows in a digital paradigm and exposes the capability for constructing big data sets of reusable materials, digitally available, for sharing and organizing material harvesting.

Keywords. Computer vision; material database; automation; reclaimed material; digitalization.

1. Introduction

At present, the construction industry is the 'number one' consumer of global raw materials (World Economic Forum and The Boston Consulting Group, 2016, p. 12) while being one of the biggest producers of waste in the EU, where it accounts for approximately '25% to 30% of all waste generated' (Construction and demolition waste - Environment - European Commission, 2019). The construction industry is facing a waste management issue compounded by a near-future resource scarcity problem; consuming more than what we can sustainably produce. On average, humans use more than '1,5 times the resources that the planet can provide' (Jensen and Sommer, 2019, p. 24). This fact questions current material flows and supports the use of obsolete buildings as a source of second-life high-value assets and materials.

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Changing the linear material flow into a circular one will increase the material recovery rate, which is only 'one-third' worldwide at the moment, (The Ellen MacArthur Foundation, 2013, p. 17) while simultaneously reducing overall demolition and construction waste (DCW). Several medium to large scale demonstrators and frameworks of secondary use materials and circular design are being constructed, including the *Buildings as Material Banks* pilot projects in Germany (Buildings As Material Banks (BAMB2020) 2020), and *Ressource City* in Denmark (Ressource City 2020); indicating the interest in eco-innovation of the European Union with long-term programs like *EU Circular Economy Action Plan* (EU Circular Economy Action Plan 2020) and projects like *Reflow* (Reflow Project 2019).

Parallel to these developments, various digital platforms have been created for secondary use materials marketplaces; matching suppliers and buyers like *Opalis* in Belgium and *Oogstkaart* in the Netherlands. Platforms like *Building Material Scout* in Germany have put in place a more robust system connecting architects, planners, auditors, investors, manufacturers, contractors, and user operators to create integrated assessments and certifications on future projects for the use of reclaimed materials. These processes start with the data acquisition of the physical environment, creating databases where all the relevant information and specifications of the materials and components are collected and organized. However, the methods used to build up this framework require a more robust infrastructure and a highly qualified workforce presenting a challenge to the sector. Therefore, to increase the feasibility of these practices more digital workflows need to be implemented.

The data acquisition could be performed through a digitally recorded model with the aid of 3D-scanning technologies into a 3D point cloud, such as in the 'Machine Vision for Reassembly' project (TU Darmstadt, 2020), where concrete elements were extracted by geometrical properties. However, the project does not implement any automated methods for the point cloud reconstruction or segmentation process, or further considerations for material database generation. With this in mind, this work aims to bring greater automation and scale for these workflows, as well as to connect their data naturally into the design process.

Lastly, a more unconventional and contemporary approach to reuse appears in the work developed by Brandon Clifford and Wes McGee in 'Cyclopean Cannibalism, a Method for Recycling Rubble' (Clifford and McGee, 2018). The project investigates new ways of bringing back concrete and off-cut stone to the construction stream instead of crushing the material into gravel. The rubble is scanned to create a point cloud, then used to run an algorithm that finds the best fitting polygon within the overall design. Apart from formal considerations, the algorithm takes into account structure limitations and fabrication constraints. The prototype was a method based experiment that set up guidelines on how to approach the process of integrating obsolete material into new and digital construction systems. The paper presents this workflow, from digitizing data acquisition to design. It establishes a new approach that opens and integrates technological advances to demolition companies' and designers' processes to maximize material reused.

2. Methods

The process that has been developed is organized into two parts, initially focusing on generating datasets of available materials from pre-demolition sites using geometric reconstruction and automatic localization techniques, to be used both as a process and a product in a new circular market. Collections of site photography from automated drone flights are first run through image localization algorithms, detecting the presence of relevant materials and their rough locations. Simultaneously, these images are used to reconstruct the site using photogrammetry; first as a rough mesh and then as data-defined building elements. These are combined with the earlier localization data to create a mapping from which material volumes, accessibility analysis, and demolition timeline planning can be obtained. The gathered data is stored in a material database and displayed in a user interface.

The second stage employs this database with a computational prototype design tool that can be integrated into the design process for architects and construction companies. The system both matches designed components with relevant stored materials by their design requirements, as well as providing suggestions for design changes. The proposed iterations aim to optimize repurposed material utilization and cost.

3. Data Capture

Initial reality capture from the demolition site is performed in three main stages. These cover the physical collection of data, the creation of mesh representations of this data, and the localization of useful materials within these digital representations.

While higher accuracy could be found with terrestrial laser scanning systems, our method used a photogrammetry workflow, both for cost and for path planning practicality. The state of debris or clutter in a pre-demolition site would impede ground vehicles robots, while consumer-level drones can cover ground more freely.

The photogrammetry reconstruction was tested with *Agisoft Metashape* (Agisoft Metashape 2006). Among the tested area, around 200 photographs were used to reconstruct a single-height space of approximately 500 square meters, interspersed with concrete columns. To extract usable geometry, *Cloud Compare* was used for its plane fitting and shape detection features to ultimately create a mesh representation of the scanned area.

As this workflow employed 2d imagery as an intermediate step, this presented an immediate data source for use by categorization and image localization algorithms. These material-localized images can then be mapped into the mesh representation for final material estimations.

Figure 1. Images from the building inspection analyzed by Larger Sliding Kernel.

Localization is performed by combining many small image classification jobs on a sliding subpatch, producing a localization map at roughly 25% the resolution of the original image, where the patch size matches the standard resolution of the training set. The classifier uses a Stacking Ensemble Learning system, combining the results of a Bag of Visual Words (BoVW) classifier with simpler Local Binary Pattern and Hue/Saturation based classifiers, which helps avoid weaknesses in each individual classifier's result. The BoVW system uses the GFTT feature detector and BRISK descriptor algorithm for generating descriptions of a patch. At the training stage, a representative subsample of all found descriptions were clustered into 512 codewords; for which each classification has an expected histogram concentration. Classification is then performed by comparing the codeword histograms between the image patch and each category.

The Local Binary pattern analysis uses 24 input points at a diameter of 8 pixels, resulting in a simple histogram of patterns present used as input for a Support Vector Machine model. Likewise the Hue and Saturation channels are reduced to size 16 histograms and used with a separate SVM model.

Table 1. Categories and training scores.

Category	Brick	Concrete	Metal	Wood	None
f-1 Score	0.96	0.97	0.96	0.94	0.94

F-scores for categorization among the test set is shown above. While the model performs well against the compiled dataset, presently there are still issues with generalization and noisy results when recombining patches into a localized result. Improvement of the compiled dataset is ongoing, as most existing publicly available image sets don't include imagery relevant to our categories, and image sets that do include more material categories (such as MINC) focus on interior finishes and fit out rather than the structural layer.

4. Material localization environment

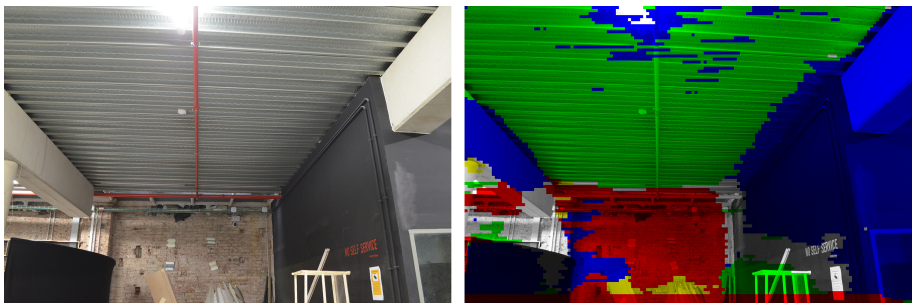

Figure 2. Material Localization.

After the image-based material localization is performed (see Fig 2), the imagery is reconstructed into a color coded point cloud (see Fig 3). The subsequent dense cloud is overlaid and measured in proximity with the reconstructed textured mesh and component segmentation, creating associations between e.g. the ceiling plane and the metal category (See Fig 3). Looking at the back wall element for instance, we look at the percentages of the material-representative colors in their mapped textures, with red for bricks, green for metal, blue for concrete, yellow for wood, and grey implying no classification. For this wall the percentage of materials in the element was as follows (with a threshold of 0.5 for each color): bricks: 48.8%, metal: 7.6%, concrete: 5.3%, wood: 7.2% and others = 31.1%.

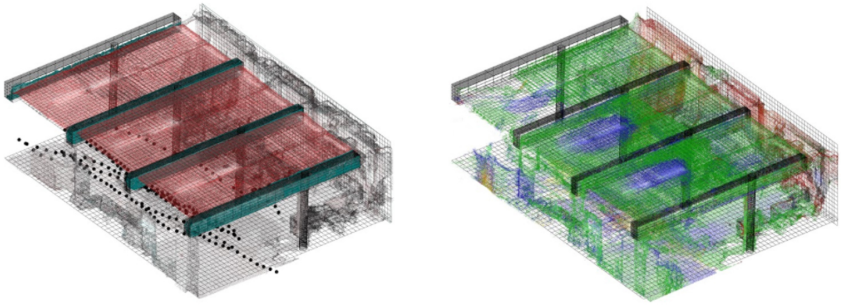

Figure 3. The isometric drawing on the left shows the original point cloud, camera locations from the imagery, reconstructed cleaned quad mesh and component segmentation. The drawing on the right shows the dense point cloud from the color coded image localization images.

Lastly a user interface was built to have more control over the information gathered. This interface includes a search bar for components and materials, once, for example, a “brick wall” is found, several information appears at the side bars (See Fig 4), showing the geo-located photographs and material localization imagery related to that material, along with other types of data like area, volume,

quantity and precision of the localization for that particular searched material. This tool can potentially be applied in demolition companies to further develop deconstruction processes creating a better building material report.

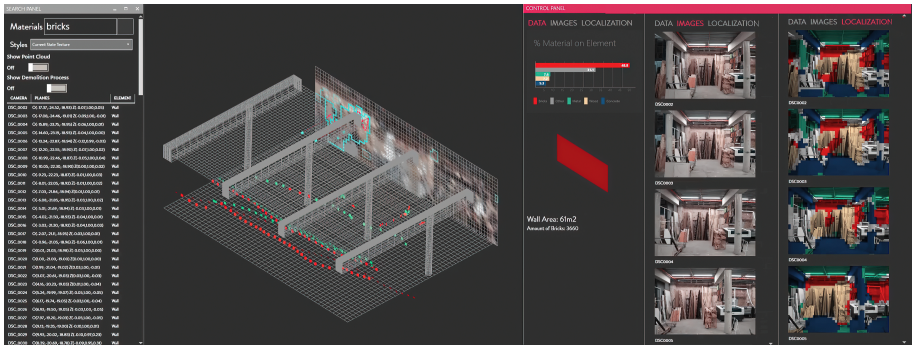

Figure 4. The user interface serves as a three dimensional environment displaying all the dataset gathered during the data acquisition from the building.

5. Design from scarcity

Once a system of data gathering and storage has been instituted, this work proposes methods for integrating, access, and previewing of this information into the computer design workflow.

The system for the design tool has been built specifically for a case study that speculates on recovering wooden beams from the "Institute for Advanced Architecture of Catalonia" (IaaC) roof structure and incorporates the recovered material in a new solar protection system for facades.

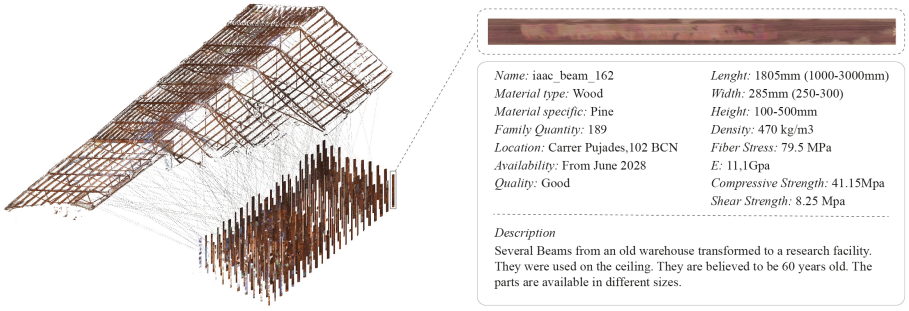

Figure 5. IaaC Roof Dataset.

In the first step the designer inputs an adaptable design and chooses a specific range of data to use in their project, adjusting the applied slice based on several constraints. The material interface focuses on presenting spatial features for geometric constraints, material specifications for structural performance analysis, and site localization for shipping cost estimation. The chosen subset is previewed

live as the user adjusts parameters.

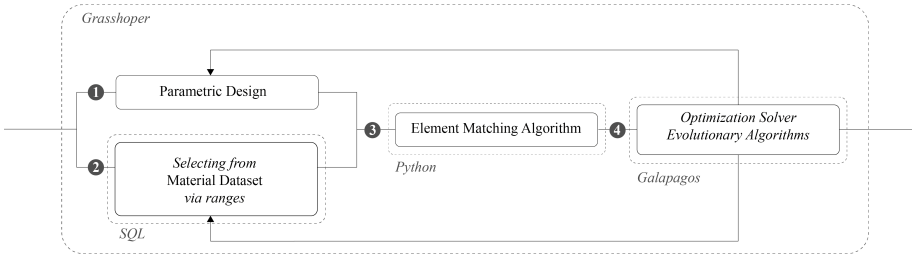

Figure 6. Circular Design Workflow.

The second step is the development of a matching algorithm. Using the Grasshopper computational design environment, a system was developed that reviews stored materials in the library and matches them with the design requirements. As each element in the design is compared with the dataset, there are three possible results: First, it may find a direct match within a certain tolerance. Alternatively, a larger piece may need to be cut down to match, and the resulting cutoff added back to the dataset. Finally, the dataset may be unable to provide the necessary element and a new-stock element will need to be procured.

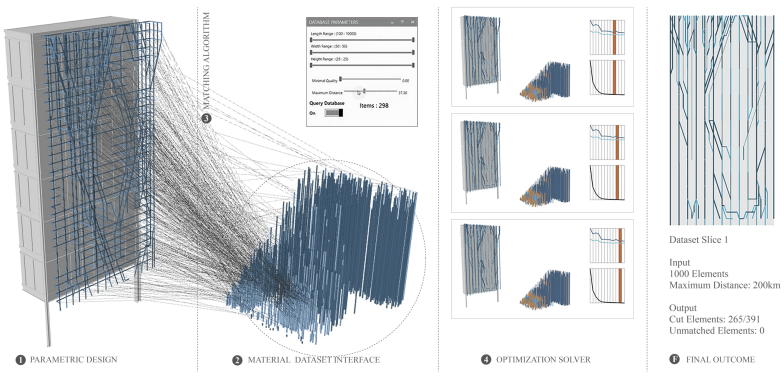

Figure 7. Case Study Process.

With the goal of an optimal density of reused material, the design approach features a degree of flexibility by adjustment of certain parameters. When an iteration of the design is submitted to the system, the materials calculated for its construction are matched up with the available items from the material dataset. The efficiency of this mapping, along with a resulting structural simulation of the resulting configuration, is used as a guiding fitness value for gradually adjusting and optimizing the design.

Finally, for the optimization, a three-dimension genetic algorithm applies small

translations to the geometric inputs of the facade and minimizes a total fitness value calculated from the previous analysis. Inputs are weighted to favor efficient reuse first, with the structural results only disqualifying an iteration if the system proves to be very unstable.

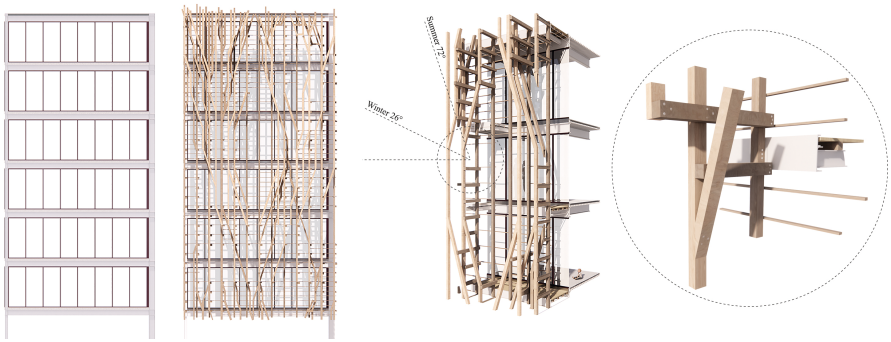

Figure 8. Existing facade and new solar protection system made with recovered wood.

6. Results and Discussion

6.1. MATERIAL DETECTION

Currently our material detection is trained for four common and generic categories: wood, concrete, steel, bricks. Ideally, the classes will be split further based on the specific of recovery, e.g. wooden flooring vs wall studs.

There are also common false-positive situations that should be trained against - e.g. concrete masonry units would occupy their own reuse profile not currently in our system, but to a computer vision system share common features both with cast concrete and brick elements.

6.2. MATERIAL ANALYSIS

The material analysis developed for the case study is composed mainly by visual inspection. Initial research towards material analysis is currently being performed using computer vision and depth camera systems to identify features such as knots, fractures and nail holes, and locate degraded areas based on surface roughness.

In most cases, post processing of the materials is necessary to remove their connective elements (e.g. nails, mortar, bolts). Automated systems for this processing would require specifically developed workflows in sensing and actuation for each type of connection.

6.3. DESIGN APPROACH

The current test-case of using rectangular extrusions with very few irregularities with dimensional data creates a proof of concept for the overall desirable system. This study case clearly relates a sparse and locally defined dimensional dataset from upcycle wood pieces to a generative design workflow. Further

explorations into this particular workflow can create a need for different types of assemblies novelty in design for disassembly strategies when shape recognition and shape matching come to play in the dataset. Lastly, as more factors such as environmental impact or recovery cost are calculated, more specific machine learning tools would also be incorporated to help the user analyze the breadth of information and meaningfully appraise the results.

6.4. LIFE-CYCLE AND MATERIAL VALUE

While the study case of the research specializes in the utilization of wood for the design prototype for the sake of speed of the tests and machinery available, the value of other materials are recognized similarly in ecological and economic potential impact. The value of a reinforced concrete wall element is some '50 times higher per ton than the value of the gravel' into which it is currently broken down when buildings are demolished (Jensen and Sommer, 2019, p. 24), because of the cost of new labour and energy (extraction, transportation, manufacturing and assembly) needed to build a new component.

When repurposing material it should be taken into account the different materials layers, for example differentiate the guidelines for the use of recycled concrete on the material level, and create an approach for reuse on the component level. At the same time a tracking system should be implemented to monitor when a material changes its location, product finish or where repairs might be needed to secure its quality when being reused in a new construction. This active monitoring will give the best status of the current state of the material increasing the robustness and durability of the system. This implies a systemic change, going from an analog categorization and assessment of pre-demolition or ready-to-disassemble sites to an intelligent planning tool that documents the quality and reliability of the components and assemblies for reuse, thereby verifying an endured market value of the buildings assets.

7. Conclusion

In developed countries, '85% of the buildings that will still be standing in 2050 have already been built' (Jensen and Sommer, 2019, p. 7), proving there is a significant need for more robust protocols for material digitalization of the already constructed environment, and most specifically, buildings. Through this research, a more intelligent and resilient system has been proposed for selective and partial disassembly of building components.

The architecture and construction sector has not presented a thorough investigation on how to use technological advancements to extract material information from existing buildings before considering the development of new ones. This research adds critical knowledge towards acquiring and using currently available assets within an automated data collection that could be plugged into existing powerful second-life material sharing platforms. The presented workflows complement each other; starting from the scanning of the physical demolition site, to data collection and elements organization, and finally its connection to a new design. Within this investigation, it has been demonstrated

that a relationship can be established between a dataset and the design principles of reusability. The proposed workflow is an exchange between generative design options and upcycled resources availability, constantly evaluating the designer intent and the building performance. The overall configuration follows a scarcity from local specificity, adding new information towards the challenge of form follows sparse availability.

Lastly, the paper displays a set of tools that can support redefining material flows in the construction industry. Following through the whole design and construction process the problem has been holistically approached by merging technologies in the process of detecting, sorting, manipulating, and reusing the recovered material.

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The structure analysis is performed employing *Karamba* and the evolutionary solver implemented is *Galapagos* created by *David Rutten*.

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