

Construction Operation Assessment and Correction using Laser Scanning and Projection Feedback

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Abstract –

Lean construction (LC) and Building Information Modeling (BIM) support an integrated vision for short cycle plan-do-check-act cycles of planning and control in construction. However, operations control tasks, such as delivery of design information to the field, monitoring, progress evaluation and error detection are still largely manual and thus time-consuming, costly and error-prone. Innovations in construction technologies can be applied to reduce cycle time, waste, construction errors and the rework that necessarily follows. In this context, we propose application of a projection and scanning technology to provide workers with real-time information and feedback regarding the quality and accuracy of their handiwork. The goal is to achieve proper quality in the first iteration, with fully automated inspection, and no rework.

As a proof-of-concept, we demonstrate the system using an example of wall plastering. The result of plaster application is difficult to measure in conventional means, and errors are difficult to detect. Our system monitors the progress of the procedure (Field-to-BIM), evaluates the surface flatness and projects corrections onto the surface itself, after optimizing with respect to industry standards and tolerances (BIM-to-Field). We demonstrate the concept in an experimental setup using a Trimble™ TX8 laser scanner and an angled adjustable projector. The results show high precision detection of wall flatness deviations, of up to 2 mm accuracy.

Keywords –

Building information modeling; construction; technologies; Data acquisition; Sensing/recognition; Human Machine interaction

1 Introduction

Lean construction (LC) and Building Information Modelling (BIM) support an integrated vision for short cycle plan-do-check-act cycles of planning and control in construction [1]. LC aims to maximize the value and eliminate the wastes in the construction process while BIM supports closer collaboration among project teams during the design and construction phases. Yet thorough implementation of the potential remains elusive because manual methods of information delivery from BIM-to-field (*a process to automatically transfer product and/or process information from BIM environment to construction field*), and of monitoring operations in the field and reporting the data to the Information Technology (IT) systems (*Field-to-BIM: a process to automatically collect/collate raw data from construction field, to interpret the data and store situational awareness information in BIM environment*), are costly, time-consuming and error prone.

IT, BIM and other construction technologies (3D scanners, sensors and cameras, etc.) can be applied to automate these information delivery and collection tasks. Especially noticeable is three-dimensional laser scanning technology which is widely used around the construction industry in tasks like mapping buildings and creating detailed as-built models, deterioration tracking, quality assurance and progress monitoring. Laser scanners provide fast, extremely detailed, easily manageable information about their surroundings in the form of point clouds. These data can then be processed for useful as-built information to be recorded and organized. Point cloud processing is possible using proprietary software tools but unfortunately, their abilities are limited and sometimes not accurate enough. Where the use of laser scanners is task-specific, the algorithmic support must be tailored to meet the unique requirements.

In this paper we demonstrate the use of terrestrial laser scanning technology and image projection as a proof-of-concept for parallel, short cycle time control of a construction operation. Figure 1 summarizes the flow of the presented proof-of-concept demonstration. The specific use-case is a wall plastering operation, and the demonstration includes monitoring and quality assessment. We implement our algorithmic approach to track the progress of construction while detecting errors and suggesting corrections, all in near to real-time. We showcase the positive effect of information transfer from site to BIM using laser scanners and data processing, and from BIM-to-field by projecting our results, in the form of images, using standard projectors. We demonstrate our results with a small-scale experiment, performed in a rectangular room, defining one of its walls as our target wall.

2 Related Work

The following sub-sections discuss the implementation of construction tech and computer vision for on-site data collection, monitoring, and information projection.

2.1 Construction Technology Integration for Automated Site Monitoring Systems (Field-To-BIM Data Gathering)

The construction industry, to date, has many construction technologies innovations. Many research papers have discussed a variety of technologies with potential for improving operation control. Lee and Choi presented a study of combination between laser scanning and imagery for building reconstruction purposes [2]. Shih and Wang reported a laser scanning system for controlling the dimensional compliance of finished walls [3]. Gordon, Lichti et al. discussed the results of using the laser scanning for structural health monitoring [4]. Biddiscombe discussed the uses of laser scanning for controlling as-built dimensions [5].

Akinci, Boukamp et al. used spatial raw data gathering from the construction field, integrated the collected data into the project models, and developed a formalism for pro-active QA/QC construction for defect detection [6]. Ordóñez, Arias et al. proposed an image-based approach for controlling dimensions of flat elements, but it requires significant human input [7]. Bhatla, Choe et al. used a 3D laser scanner to capture and record the site progress data. The results were proven as more accurate than traditional site progress tracking [8].

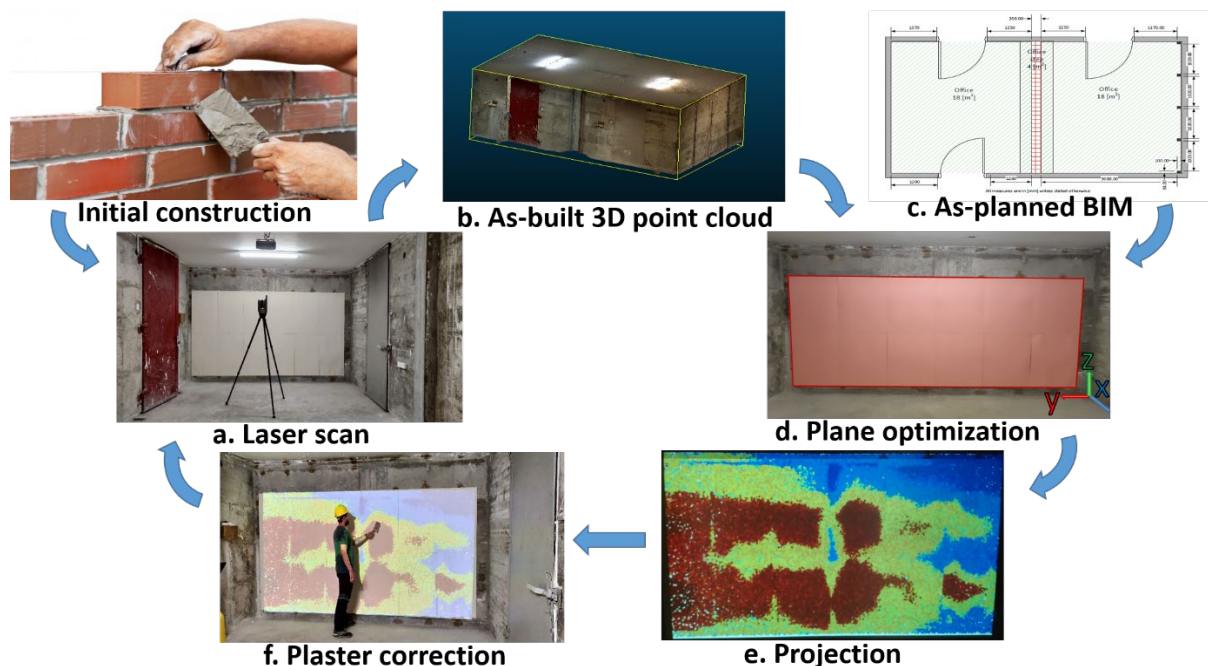


Figure 1. Flow of proof-of-concept demonstration. (a) Begin by scanning for progress detection, (b) obtain high accuracy as-built point cloud, (c) compare to the as-planned BIM data and detect errors, (d) cost optimization, (e) output projection, (f) correction of errors in accordance with image projection on the wall. Repeat scanning for updating status and next flow iteration until reaching termination at satisfactory conditions.

Braun, Tuttas et al. presented a test case of on-site progress tracking and recording. The presented work discussed ways to transfer collected raw progress data to BIM workspace using point cloud technology for construction control purposes [9].

Pučko, Šuman et al. presented a method where site works are constantly monitored, instead of scanning of a whole building under construction from time to time [10]. As a result, the as-built BIM model is continuously updated during the construction cycle. The presented method depends on low precision 3D scanning devices which are small enough to fix on workers' helmets and on the active machinery as well. The 3D scanning devices allow workers to capture the workspace and work that has been done, inside and outside of the building, in real-time. The recorded data include workers' locations and capturing time. The captured point-clouds were imported to 4D as-built BIM models. Then, the comparison between 4D as-built model with 4D as-planned model enabled identification of the differences between both models and the deviations from the time schedule as well.

Current approaches to control surface flatness are inefficient. Bosché and Guenet proposed an automatic surface flatness control process using laser scanning and BIM [11]. Their approach applied straightedge and F-Numbers methods. Their experiments demonstrated the suitability of laser scanning for standard dimensional controls and validated its quality and efficiency benefits vis-à-vis traditional measurement approaches. Valero, Forster et al. presented a method for automated defect detection and classification in ashlar masonry walls using laser scanning and machine learning [12]. The algorithm they developed identifies material defects and discoloration. Neither of these methods included in-situ feedback to the workers, as our system does.

Clearly, laser scanning technology is one of the leading methods for spatial data gathering. Past success encouraged us to choose this technology for our experiments.

2.2 BIM and Construction Technology Integration for Information Management

BIM and construction technology integrated applications are still not very common. Alizadehsalehi and Yitmen [13] and Patraucean et al. [14] discussed the impact of the combination of data capturing techniques with BIM in construction companies; both discussed the point cloud based method for creating as-built BIM models. The results show that site surveying for work done on site could be prepared in less time and more accurately by overlaying as-designed BIM models with 3D as-built captured BIM models, than by manual surveying.

Bosché, Ahmed et al. discussed the value of integrating Scan-to-BIM and Scan-vs-BIM techniques

for construction monitoring [15]. They used laser scanning and BIM in a unified approach for automated mapping of as-built vs. as-planned MEP works to monitor earned value (work done), and to assist in delivering as-built BIM models from as-designed ones (performance measurement). Among the incremental improvements of their approach: (1) recognition and identification of objects not built at their as-planned locations; and (2) consideration of pipe completeness in the pipe recognition and identification metric.

Kim, Chen et al. presented a navigation and object recognition method that was implemented and tested with a custom-designed mobile robot platform, which uses multiple laser scanners and a camera to sense and build a 3D environment map [16]. The study shows that the 3D colour-mapped point clouds of construction sites generated were of sufficient quality to be used for many construction control applications such as construction progress monitoring, safety hazard identification, and defect detection.

Kopsida and Brilakis have evaluated different methods for reality augmentation by BIM model information and came to the conclusion that sparse 3D data leads to the most robust results when as-built and as-planned information overlay is requested for progress management [17].

2.3 Construction Technology Integration for Product and Process Information Transfer (BIM-To-Field)

To date, Augmented Reality (AR) has rarely been applied to construction control. However, it has the potential to improve the efficiency and quality of construction work by providing digital content on top of physical surface views to assist teams in the field [18]. Different approaches to integration of BIM and AR in construction have been proposed. Yang and Ergun discussed integration of BIM and AR, showing how semantic information can be transferred from a BIM platform to an AR system to improve the user visualization interface [19]. Williams, Gheisari et al. proposed an approach for BIM model translation to be used in a mobile AR application, which improves the direct use of BIM information through AR on-site [20].

Degani et al. presented an integrated BIM-Robot-AR system with self-localization method using data from distance sensors to find the probable pose (position and orientation) of system in an identified space [18]. The study showed the accuracy of self-localization and the system's feasibility for accurate projection of BIM model data directly onto physical surfaces in the field. In this work, we extend the capability of that system, focusing on two-way communication of information, from BIM-to-field and from field-to-BIM.

3 Methodology and Algorithms

3.1 Initial Assumptions

To reduce extra effort for unlikely scenarios, a few assumptions were made. The main assumption, regarding the operational area, is a rectangular shaped room. The room is assumed to have four walls, a ceiling and a floor, six planes in total, all perpendicular (or parallel) to each other. The origin of the coordinate system is assumed to lie within the room, in the geometric center. It is also assumed to be almost empty, without furniture or clutter. These assumptions help organize the initial conditions and partially assure consistency in the point clouds received after scanning the operational area. In previous work, we have demonstrated the ability to localize a moving AR projector using Markov localization [18]. In this work, we simplify by assuming a static projector in a known location.

3.2 Laser Scan Pre-Processing

To achieve satisfactory conditions for working with the point cloud recorded by the laser scanner, each scan needed to be pre-processed. Each scan was acquired from two scanning stations and registered manually. The use of two scanning stations enhanced the overall accuracy of the scanned data. The stations were located opposite one another, one on each side of the operation room. Combining two scans roughly evens out the point density of the entire cloud, since the point spacing grows linearly with the distance between the scanned object and the laser scanner. Using Trimble Realworks™, the point clouds of the two stations were manually registered together and aligned with the X, Y and Z axes. Later, the alignment is manually refined as discussed in the next section. The point cloud was down-sampled by a factor of 10, yielding a dataset that was easy to work with without compromising accuracy. A RANSAC algorithm was applied on the points and a normal was estimated for each point based on 10 of its nearest neighbors [21]. This normal represents the plane on which the point is assumed to lie. Finally, the point cloud's center of mass was calculated by averaging all the X, Y and Z coordinates of the points. With two stations, each with its own deviations, we could refine the alignment between the two. In the next section, we will describe the process of wall detection. This is needed for two reasons: first, we impose no requirements or constraints on the position and orientation of the laser scanner during the scans; second, as we are capturing the status of the operation at partial progress, with possible errors already present on site, we can use the as-planned information only as reference while making sure the detection of walls, errors and progress status are correct.

3.3 Wall Detection

Once the point cloud had been pre-processed, the walls were detected, and a specific target wall was identified. The walls, or planes, of the point cloud were detected using a clustering algorithm, K-means [22]. The clustering algorithm receives the normals of the points as input. The points were then divided into six clusters. Each cluster represented one of the walls, the floor, or the ceiling. The algorithm also assigns a center of mass (COM) to each group, which is not necessarily a member of the cluster. This COM was then validated by averaging all X, Y and Z arguments of the normal of the points related to each cluster. The central normal of each cloud, at this stage, has slight deviations from the absolute Cartesian axes. This can be fixed effortlessly by calculating a transformation between the absolute axes and the current plane normals. This transformation was then applied to the entire point cloud, aligning it with the absolute coordinate system of the as-planned information. For simplicity's sake, the experiment focused on a single, randomly chosen wall called the 'target wall'. The wall was identified by its ID output of the k-means algorithm and separated from the point cloud. At this stage, all elements of the room are known and identified. Any construction progress made with respect to previous scans can be updated and registered. The process is detailed in algorithm 1.

Algorithm 1: Wall Detection

Input:

- Scan of the room [PCL file]
- Target wall normal vector [float vector]

Output: Target wall point cloud aligned to wanted vector

Constants:

- NUM_OF_WALLS
 - WALL_NORMALS
-

```

Mean_PCL = avg{ PCL (x), PCL (y), PCL (z)}
Displacement = -1* Mean_PCL
Normals = find_normals(PCL)
Normals = rotate_normals_towards Mean_PCL
Walls = cluster(Normals, num_of_walls)
for wall_index := 1 to num_of_walls:
    normal := avg{ Normals (x), Normals (y), Normals (z)}
    Rotation = angle(normal(1), const_normal(1))
    PCL = translate and rotate(Displacement, Rotation)
for wall_idx := 1 to num_of_walls:
    if wall_normal == target_wall_normal
        target_wall_idx = wall_idx
        target_wall_PCL = PCL (wall_idx)
    rotate (target_wall_PCL [0,0,1])

```

3.4 Plane Optimization

Two main features of our proposed system are error detection and correction. After detecting the error, a cost assessment must be performed for the repair operation. To estimate this cost, we must know how different the current state is from the desired, optimal one, i.e. how

severe the detected errors are. Note that the optimal result does not necessarily conform to the originally designed state defined in the BIM model. In certain situations, considering underlying deviations from the original design, such as deviations in the concrete or block face, an optimal result may be one that can be achieved economically while still satisfying design performance conditions (such as planarity, verticality). The decision needs to be made simultaneously with the construction operation. As part of our proof-of-concept experiment, we are dealing with monitoring and correcting plaster application. Our goal is to supply real time improvement suggestions and we want it to be optimal in terms of cost. A tight constraint we face is the fact that the wall must be perpendicular to the floor. In 3D terms, we are left with two degrees of freedom for plane adjustments, keeping the plane's normal parallel to the floor. Figure 2 shows in top view, the exaggerated features of the wall surface with a blue line and the red line is the optimal plane.

As can be seen in Figure 2a, one option is to move the plane along its normal, basically controlling the "d" parameter of the plane equation. The equation of a plane in the three-dimensional space is:

$$ax + by + cz + d = 0 \quad (1)$$

In Figure 2b and Figure 2c the second degree of freedom is presented – rotating the plane about the Z axis. Each one of the two described changes in the plane's location results in a different topography of protrusions and depressions. Figure 2d shows the grid of cost calculation. The calculations are demonstrated in algorithm 2.

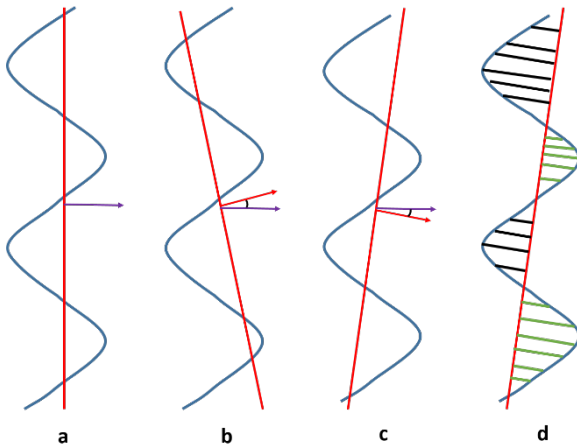


Figure 2. Surface flatness optimization. (a) Nominal plane, (b) rotated plane to positive angle limit, (c) rotated plane to negative angle limit, (d) visualization of grid for cost calculations.

Algorithm 2: Cost Optimization

Input:

- Target wall point cloud [PCL file]
- Nominal plane [plane parameters]
- Filling up cost [float number]-FU_cost
- Shaving off cost [float number]-SO_cost

Output: optimal plane [plane parameters]

Constants:

- Target wall absolute normal vector-TWANV
- Industry tolerance-IT
- Design constraints-DC

```

DC_vec := [0:0.001:DC]
IT_vec := [-IT:0.001:IT]
Optimal_plane := Nominal_plane
Fill_up_cost := 0
Shave_off_cost := 0
Cost_TOT = max(FU_cost,SO_cost)*num_of_PCL_pts
for D in DC_vec:
  for Angle in IT_vec:
    Curr_plane := [Angle, D]
    Fill_TOT = (num_wall_points > curr_plane)*FU_cost
    Shave_TOT = (num_wall_points < curr_plane)*SO_cost
    Curr_cost := Fill_up_cost_TOT + Shave_off_cost_TOT
    If Curr_cost < Cost_TOT:
      Cost_TOT = Curr_cost
    Optimal_plane = Curr_plane

```

4 Experiment

4.1 Experimental Setup

The experimental setup includes a rectangular, 32 m² room (8 m x 4 m), a laser scanner (Trimble™ TX8) and a standard projector. As can be seen in Figure 3, the room has bare, unfinished walls, a convenient state for benchmarking the accuracy of the laser scanner. The room is rectangular, and all of its parameters are in accordance with the initial assumptions given in section 3.1. The purpose of the experimental setup is to construct a proof-of-concept system that can monitor, assess, and evaluate a wall plastering operation. The system is required to perform in near real-time and provide a complete start-to-end solution. System demands include progress monitoring and surface quality assessment by error detection and optimal error correction. Three visual steps of the flow can be seen in Figure 4.

4.1.1 Indistinguishable Discrepancies

A reasonable assumption is that errors of plaster application are difficult to notice with the naked eye. Imperfections will usually be due to gradual straying from a desired plane, without rough changes or noticeable edges.



Figure 3. Experimental room

In these cases, our system is most useful, which was the motivation of this experiment. This experiment is performed in the same room, but with a target wall with thin cardboard sheets attached to it as shown in Figure 5a. The sheets are fixed adjacent to one other and cover most of the surface of the wall. The main purpose of the setup was to simulate a gradual drift of the plaster surface instead of rough, highly visible discrepancies. The target wall imperfections were also taken into consideration, but their effect was negligible as the optimal plane placement is fixed with respect to absolute X, Y and Z global coordinates.

4.2 Experimental Flow

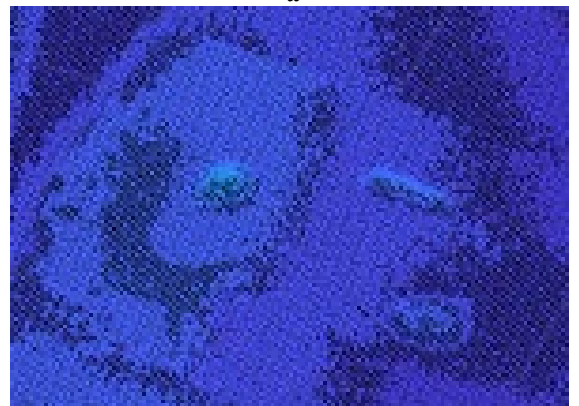
The experiment is used to show the full extent of the construction operation. The main target of our proof-of-concept experiment was to demonstrate the cycle of construction work monitoring, error detection, error correction and status update. The experiment comprised a few stages, which are discussed in the next subsections.

4.2.1 First Scan

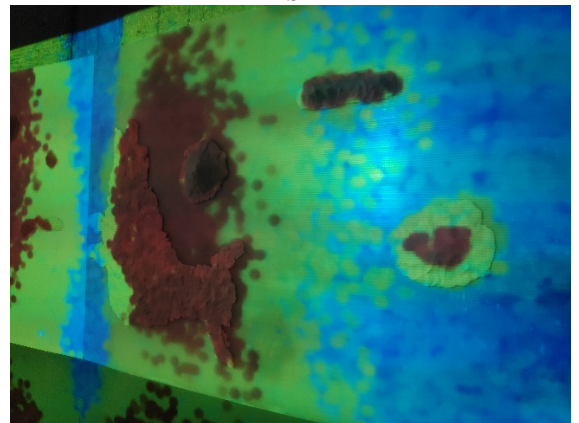
The first scan was performed to calibrate and prepare the system. Two scanning locations ("stations") were used as described in section 3.2. Each scan was performed with highest accuracy setup of the laser scanner. For the Trimble™ TX8, used in this work, the point spacing at 30 m is 5.7 mm. Each scan took about 10 minutes. Both stations were registered using a proprietary software tool that receives manual input – the user needs to mark three pairs of locations on both scans. The same scan setup was performed twice, both in an illuminated environment and in complete darkness. The scans were compared, and the results were similar - both point clouds met the requirements of section 3.2 and had equal errors. In accordance with sections 4.1.1 and 4.1.2, a wall was chosen for demonstration purposes and two types of plaster lookalikes were applied.



a



b



c

Figure 4. Using modelling clay to simulate discrepancies in the wall. (a) Hand sculptured modelling clay, (b) point cloud of the target wall, (c) projection on the target wall.

The cardboard sheets were placed on the wall to simulate low frequency plaster irregularities and the play dough was placed to simulate rough inaccuracies and to benchmark the laser scanner accuracy. People find it difficult to identify small inaccuracies in a plastered wall. This is why the cardboard setup was chosen for the rest of the experiment.

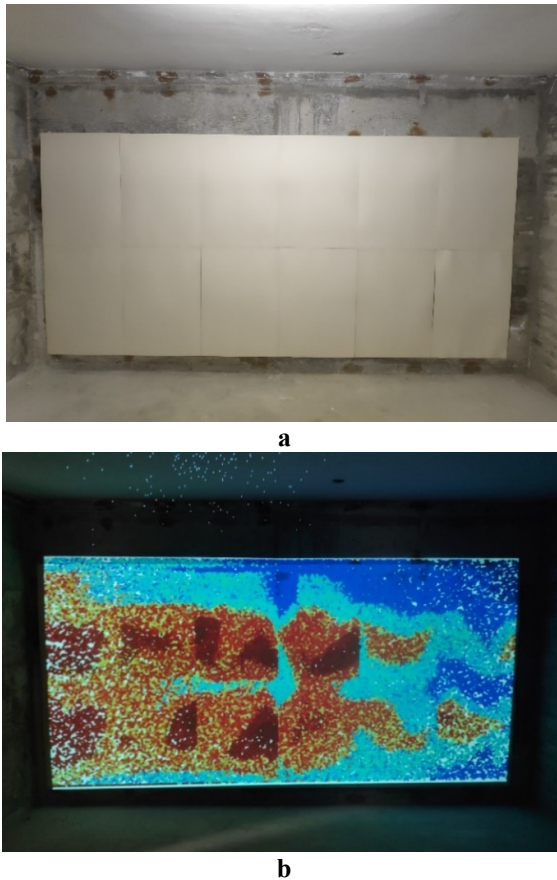


Figure 5. (a) Using cardboard sheets attached to a target wall to simulate minor discrepancies in the wall, (b) error correction projection on target wall.

4.2.2 Data Processing

Data processing was performed as described in sections 3.2 and 3.3. After extracting all the points of the working wall, a mean normal was calculated and a plane was fitted by this normal. This was the nominal plane that identified the current baseline target wall from which the optimization calculations could start.

4.2.3 Optimization

After making sure that the nominal plane was perpendicular to the plane of the floor, an optimization process was initiated. With the current state of the target wall, an optimal plane was derived from the optimization process. In some areas the optimal plane was "submerged" in the target wall and in others – raised above it. This was evident in the projected image as different areas had different colors.

4.2.4 Projection

A topographic map was produced, relative to the direction of the optimal plane normal. A manual calibration of the projector's location was done in order to project the image on the wall with the correct perspective. We have previously demonstrated the ability to localize a projector based on an image captured by a camera in a known location [18]. As can be seen in Figure 5b all areas on the target wall that needed to be shaved off were colored in shades of red and the ones that needed to be filled up with plaster were colored in blue. The color map helped with visualizing 3D data in a 2D image. The gradient of colors was equally spread between the "highest top" and the "lowest bottom". All the high contrast areas that can be seen in Figure 5b are edges between sheets of cardboard or between a sheet of cardboard and the wall itself.

4.2.5 Additional Iterations

The cardboard sheets were flattened to simulate a flattening procedure in accordance with the projection. The room was then scanned once again, with identical parameters as the previous time. The second cycle was about finer detail correction, in comparison to the first one. The scan was similarly processed, and another complete flow cycle was carried out, resulting in a new heat map. The heat map was projected using the same static projector and both iterations included high precision projection accuracy with offsets no more than 1 cm. Within the projected image, the measured errors had a mean of 2 mm. The projection process was not optimized and can be improved in future executions. This procedure can be repeated as often as needed, terminating once the work complies with some predetermined accuracy threshold.

5 Conclusion

In this work we have successfully demonstrated practical implementation of a conceptual short cycle of construction control composed of progress monitoring, error detection and optimal error correction. We have planned and carried out a small-scale experimental setup dealing with wall plastering assessment.

The experiment indicated that maximal accuracy is within reach and is restricted only by the capabilities of the hardware in use, i.e. laser scanner. In our model and scan setup we were able to achieve 2 mm accuracy of scan that was reflected on the measured results. We have iterated over two complete cycles of the flow, improving the plastering quality with every iteration. In each cycle we measured the distance between the projected elements and the real ones before mending the work.

We assume that the principles demonstrated by our proof-of-concept experiment can be applied to other

construction operations, and that our bi-directional workflow can help automate operations. We stress that from a technological perspective, each task must be treated in a different manner with appropriate algorithms. The robustness of the specific implementation is restricted to the task at hand and cannot be easily transferred to other construction tasks. We plan to integrate automated localization for the projector in future work.

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