Drywall State Detection in Image Data for Automatic Indoor Progress Monitoring

C. Kropp , C. Koch and M. König

Chair for Computing in Engineering, Department of Civil and Environmental Engineering, Ruhr-Universität Bochum, Gebäude IC, 44780 Bochum, email: christopher.kropp@ruhr-uni-bochum.de

ABSTRACT

In the context of interior finishing works, delays occur frequently to the initially planned schedule. Since disturbances are unavoidable, a continuously acquisition of the construction progress is essential. Current practice of acquiring the actual construction progress is performed manually and therefore work-intensive and time-consuming. There are approaches that base on the acquisition of image and video data to derive the current state of objects. Drywalls are a very particular case of detectable objects, because the walls' extents mostly do not fit in the sensor of the camera system. Therefore, it requires image features that allow the distinction of different completion states without the feasibility of the investigation of the whole wall. In this paper, the special case of a drywall completion state determination is examined. A method is presented that deals with the automatic detection of the state. Hence, three different states, namely the installation of panels, plastering and painting are analyzed. Features are derived that allow for the differentiation of the states and a cascaded classification is performed. Therefore, a test set is created, consisting of real image data acquired from the finishing of the interior of a building. A Support Vector Machine is trained with the extracted features and images are tested against the trained classifiers to demonstrate the success of the method.

INTRODUCTION

Progress monitoring on construction sites is currently performed manually and therefore it is labor- and time-intensive. Experts need to inspect the construction site to be aware of the actual state of the building under construction. The inspection of the current state includes the acquisition, assessment and documentation of how tasks have actually been performed, as well as the comparison of the acquired data with what has been planned before and the estimation of deviations between the as-planned and the as-performed state. Especially for indoor construction sites, where scenes are separated by walls and tasks may reveal only delicate visual changes, it is essential to obtain reliable statements about the progress. Furthermore, since most of the inspection reports have the foundation of visual assessment, the grade of acquired progress data depends on the personnel's experiences and quality of measurements on a high degree (Golparvar et al., 2009).

In practice, weekly or daily paper-based progress reports are collected manually by field personnel (Roh et al., 2011). Hence, manual progress monitoring involves either a huge amount of human expert resources or inspection updates cannot be performed as frequent as required.

Increasing the degree of automation in progress monitoring is a desirable aim for leveraging the abilities of decision making. In Kropp et al. (2012), a framework was introduced that targets performing progress monitoring automatically. A mobile device is traversed through the construction site. Under the use of knowledge from schedule loaded BIM models, visual motion estimation and Inertial Measurement Unit data obtained with device integrated sensors, the actual state of objects should be stated. Within this framework, approaches for different kinds of materials and objects are required due to their individual characteristics. In this paper, the detection of the drywall state during indoor construction is considered, including three different states associated to tasks, namely installation of panels, plastering and painting of the drywalls.

BACKGROUND

For recognition of materials in construction, several approaches were recently presented. In Zhu and Brilakis (2010), a material detection of concrete in a cluttered construction environment was proposed. The method separates the characteristic color of concrete from differently colored image parts. This method works for segmentation of a specific colored material, but not for distinction of different similarly colored states. In Zhu et al. (2010), the approach of detecting concrete is extended to the detection of concrete columns. Therefore, columns with larger extents than the camera view are stitched together to achieve full visibility. This method achieves detection of a specific material and its object’s extents, but only if the surrounding area color differs to it. The texture recognition and inpainting algorithm presented in Al-Takrouri and Savkin (2010) targets on evenly repeated textures like bricks. It detects and separates different patterns in textures according to frequent and repeating image features. This method cannot be applied on drywall state detection, since patterns are not present. In Koch and Brilakis (2011), potholes are detected on an Asphalt texture. The method scans the texture of the asphalt and finds the potholes according to their characteristic properties. In Roh et al. (2011) object detection is considered especially for indoor purposes of progress monitoring. The approach detects air condition equipment and is in general only applicable for small objects with distinct characteristics.

None of the existing approaches work for the characteristics challenging in drywall state detection. The presented approaches take into consideration fixed size of patterns, the visibility of objects and materials in full extent at least in one dimension or only work in outdoor environments. Under the given conditions an approach needs to be developed for successfully detecting the correct state of drywalls.

METHODOLOGY

Drywalls and their different states during construction are usually characterized by very challenging textures. There is low structure and the appearance mainly remains in the same light color area. As well, there are none or only unintended texture patterns. Additionally, in the specific case of indoor environments, the walls are usually not completely visible in one view. Each state of the drywall completion process contains a different characterization.

Installed panels of the drywall are characterized by vertical and horizontal lines along gaps between the single panels (see Figure 1(a)). The color of the panels is usually kept light in a constant color. Depending on the direction of the light source, the intensity of the lines contrasting to the panels in the appearance of the wall in the image may vary. Moreover, dots appear at screws fixing the drywall panels to the underlying frame. In contrast, plastered (see Figure 1(b)) and painted wall (see Figure 1(c)) states appear in an even more homogeneous color space in the images and are even hard to distinguish by human perception. Plastering a wall intends to even out the surface of the wall. Thus, the plastering material is usually applied on the screws fixing the drywall to the frame and the gaps between the panels. The plastering material is as well intended to be in the same color as the panels, since the later painting benefits from low contrast to the underlying surface color. A significant difference between plastered and painted drywalls is the variation of reflection properties between the materials. Depending on the illumination, the obviousness of this difference varies strongly. Finally, painted drywalls are quite even in their color representation and only differ slightly by light changes.

a) b) c)

Figure 1. Example image of a) installed drywall panels, b) plastered drywall and c) painted drywall

The method presented targets on the distinction between the different states of a drywall completion. This method is part of a framework for indoor progress monitoring, where the first step contains motion estimation of the image capturing device. Although this step is not considered in this paper, the camera position and pose is required to be known from motion estimation. Furthermore, a schedule loaded BIM model is expected in order to be able to derive drywall extents from the 3D model and determine a Region of Interest (ROI) containing the relevant drywall as displayed in Figure 2.

Since images are taken during construction, several unexpected objects can occlude the desired drywall and thus disturb a clear view on the expected texture characteristics and disturb results. In order to remove unexpected materials and equipment like ladders, painting pots or cables, an image segmentation is performed. It uses a color based approach, since wall surface color does not change significantly over the whole extent and occluding object colors usually differ from the wall color in any state of completion. Color differences across the wall texture normally only occur through illumination changes and do not have a large effect along the visible part of the wall. The segmentation method uses a histogram of the V channel of the HSV color space along the ROI and eliminates unexpected colors (see Figure 3).

Figure 2. Example image of a drywall with original appearance (left) and BIM extracted ROI (right).

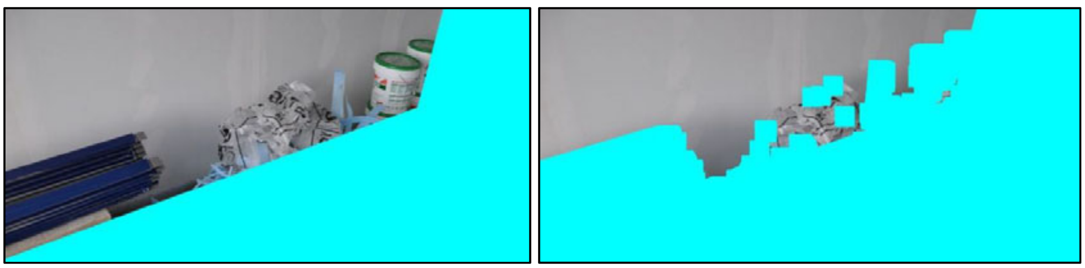


Figure 3. Example image of a drywall with BIM extracted ROI (left) and segmentation for occluding object removal (right).

For the determination of the three different considered states of the drywall completion, a cascaded approach is developed, regarding the specific characteristics of the states in each stage. The first stage focusses on the line and dot characteristics of the paneled drywall the second stage looks for difference of the reflecting properties of materials appearing on plastered walls. Summarizing the method (see Figure 4), it continues with result of ROI extraction, applies segmentation and performs two cascade stages to determine the drywall state.

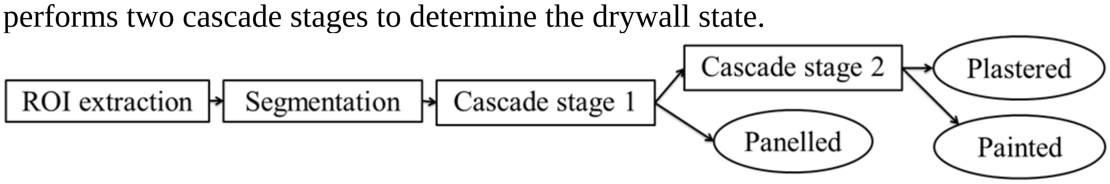
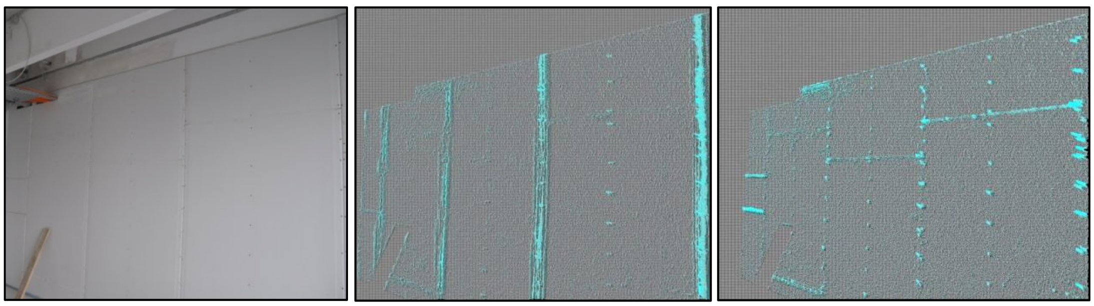


Figure 4. Method overview.

To solve the first stage, the edges that appear at screws and along the vertical and horizontal lines of the gaps between the panels are used to make a distinction between on the one hand paneled walls and on the other hand plastered and painted walls. Therefore, image features are derived allowing for these properties. In Prewitt (1970), a compass edge filter is discussed that considers the direction of edges and is able to emphasize edges in a specific direction. For that reason, two filters that target the extraction of horizontal and vertical lines are applied on the image, resulting in two edge intensity maps of the image, as illustrated in Figure 5. For each of the two maps a proportional distribution of the absolute values of the gradients $G_{vertical}$ and $G_{horizontal}$ of the image I with,

$$G_{vertical} = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} * I, \quad G_{horizontal} = \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} * I$$

is resulting in a feature. If rotated walls inside the images need to be considered, image rectification according to the estimated camera motion would have to be applied. To keep the edges sharp, a bilateral filter, as described by Tomasi et al. (1998), is applied for smoothing the noisy low light image capture. Thus, a two dimensional feature vector is extracted for each image. The intention is that paneled wall images will result in a higher percentage of edges, if edge extracting responses are regarded that are higher than a certain threshold than for plastered and painted walls. Particular thresholds need to be found for each edge map in this stage.



a) b) c)

Figure 5. Example compass edge feature extraction with a) original drywall panels image, b) vertical and c) horizontal compass edge features of ROI of wall

For the second cascade stage, class distinction is focused on increasing the contrast of the areas that are plastered to the untouched panels. To increase the contrast of the whole image, for instance by histogram equalization, has the result that the varying illumination of the image has a larger effect than the fine reflection differences that occur because of the application of the plastering material. Therefore, the Contrast Limiting Adaptive Histogram Equalization (CLAHE), presented in Zuiderveld (1994), is used for this approach. Within this equalization approach, the drywall is subdivided into smaller blocks where the pixel values are equalized due to the block's histogram of pixel values. To avoid a high influence of noise, the contrast is limited to a specific threshold and contrast above evenly distributed to block pixels.

Applying the method on the plastered drywalls has on the one hand the effect, that contrast of the differently reflecting materials increases and on the other hand that illumination differences along the extent of a wall are partly eliminated as illustrated in Figure 6. For painted walls, there are less contrast changes when applying CLAHE. Hence, the distribution of light and dark image pixels over the image has a lower range than for the plastered drywall state. This property is used for the feature derivation of the second state. Consequently, a normalized histogram is created regarding the intensity of the pixel values on the drywall and the histogram, consisting of a certain amount of bins, is used as a feature vector for class distinction.

a) b)

Figure 6. Example of a) original plastered drywall image and b) adaptive histogram equalized image

EXPERIMENTAL RESULTS

In order to perform an evaluation of the proposed method for the determination of the current construction state of drywalls, an indoor construction site was observed to obtain test data. The drywall installation was part of the construction of a research and office building. An experimental test set of images where drywalls with various states are seen were selected. Since current works within the framework regarding motion estimation are not completed, registration of the images is performed manually. In total, there were 48 images of panelled walls, 58 images of plastered walls and 54 images of painted walls. A low number of images was chosen, since the selected low level features should be tested for their generalization abilities. The image test data was divided into the three desired classes of first panelled, second plastered and third painted drywalls. For testing the first cascade stage, the positive images containing the first class were tested against a superset of images where all other states are visible. For the second cascade stage, the images of the second and third class were tested.

For the first cascade stage, compass edge distribution features from all classes were extracted. To find optimal values for the thresholds, different threshold values for the horizontal and vertical compass edges were extracted independently during the feature extraction process. Consequently, a Support Vector Machine (SVM) was trained for the first cascade stage with all images correctly labelled due to their relation to the first class and the superclass containing the plastered and painted wall appearances. The training was performed in the manner of a repeated random subsampling cross validation approach due to the relative low number of images in the test set. This includes a random subdivision into a certain amount of subsamples. For each test, one subsample was used for testing and the rest for training. This was repeated several times, each time with a different subdivision.

The test results are illustrated in Figure 7, where Figure 7 a) contains the precision, Figure 7 b) the recall and Figure 7 c) the F-measure of application of the bilateral filtering. The higher the value for the precision with higher threshold gets, the lower the recall falls, which can be interpreted as with rising quality in that part of the results, the quantity falls. The combined F-measure of 0.932 with threshold 5 for horizontal edges and threshold 17 for vertical edges delivers an acceptable result for the first stage of the recognition cascade.

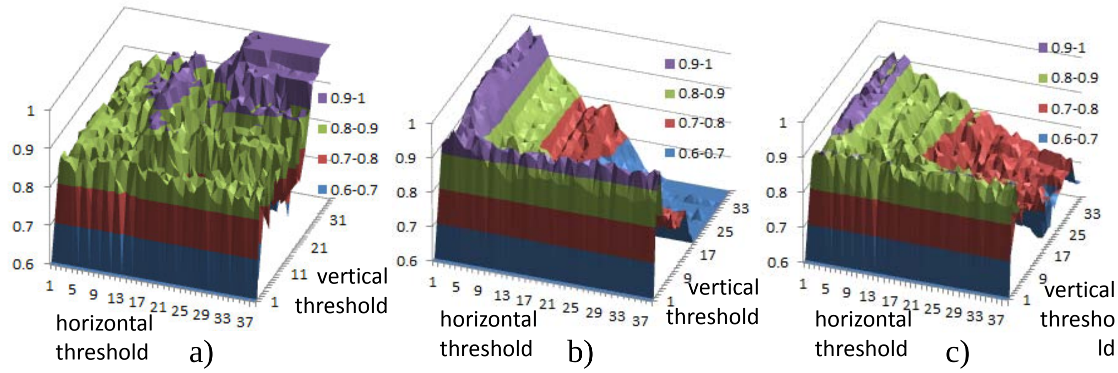


Figure 7. First cascade step testing results a) precision, b) recall c) F-Measure for different horizontal and vertical compass edge thresholds

In the second cascade stage, pixel intensity histogram features from classes two and three were obtained with various CLAHE parameters for the contrast limit. For the histogram an amount of 16 bins was chosen. A SVM is trained with the histogram features of the two classes also in a repeated random subsampling cross validation approach. The testing results displayed in Figure 8 show the development of the success of the method under different CLAHE parameters. Figure 8 a) and b) show that the precision and recall changes evenly with the same parameters. Therefore the F-measure results in Figure 8 c) shows the best value of 0.974 located with block size 33 and contrast limit 29 close to the maximum values for precision as well as for the recall of the tested parameters.

The experimental results show that parameters for the proposed methods can be obtained under which they work for each stage of the cascade. With the trained classifiers, a reasonable drywall completion state can be performed with a high accuracy.

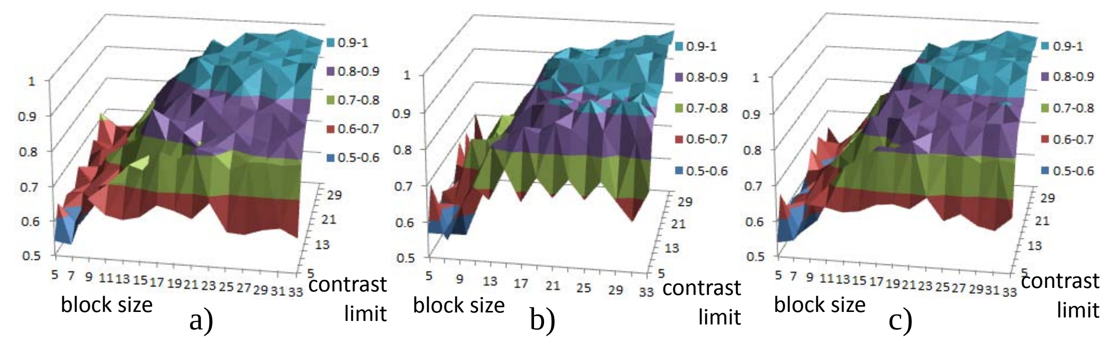


Figure 8. Second cascade step testing results with a) precision, b) recall c) F-Measure

CONCLUSION

In this paper a drywall completion state determination method under the use of image processing, computer vision and machine learning is proposed. The method deals with the automatic detection of the three different states: installed panels, plastering and painting. Edge distribution and pixel intensity histogram features for the different cascades are derived that allow the differentiation of the states and a cascaded classification is performed. For method evaluation Support Vector Machines are trained with features obtained from an image test set and the trained classifier is tested. The results for each cascade step show good performance of the chosen features and different parameters are tested to find a good parameter choice for the tested images. Hence, the proposed cascaded feature comparison can be used to distinguish between different states of drywalls. In order to proof general success of this method it needs to be tested with other drywall types and image sets. To find optimal parameters for the methods, an optimization problem needs to be issued.

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