Automated Image-based Detection of State of Construction Progress

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Introduction

Construction progress tracking, vital to a project's on-time and on-budget completion, is still manual, labor-intensive, and expensive. Here, an image-based technique is developed which automates the detection of state of construction work for indoor partitions using digital images and machine learning. This method relies on a cascade algorithm which employs a combination of bag-of-visual-words approaches and texture classification. The technique receives as input an image of an indoor partition, and it classifies it into one of the five possible states of work: framing, insulation, and drywall (installed, plastered, painted). The presented method was observed to perform robustly in highly cluttered scenes of indoor sites, and it achieves an average classification accuracy of 96%.

Related Works

- Progress detection for a *limited* number of states, while heavily relying on *manual parameter tuning* and *a priori information about scenes* [1]. Images were known to be in certain states of work.
- Detection of *objects* in the scene [2]: not robust for scene detection, changes in view point, occlusion, and varying illumination conditions.

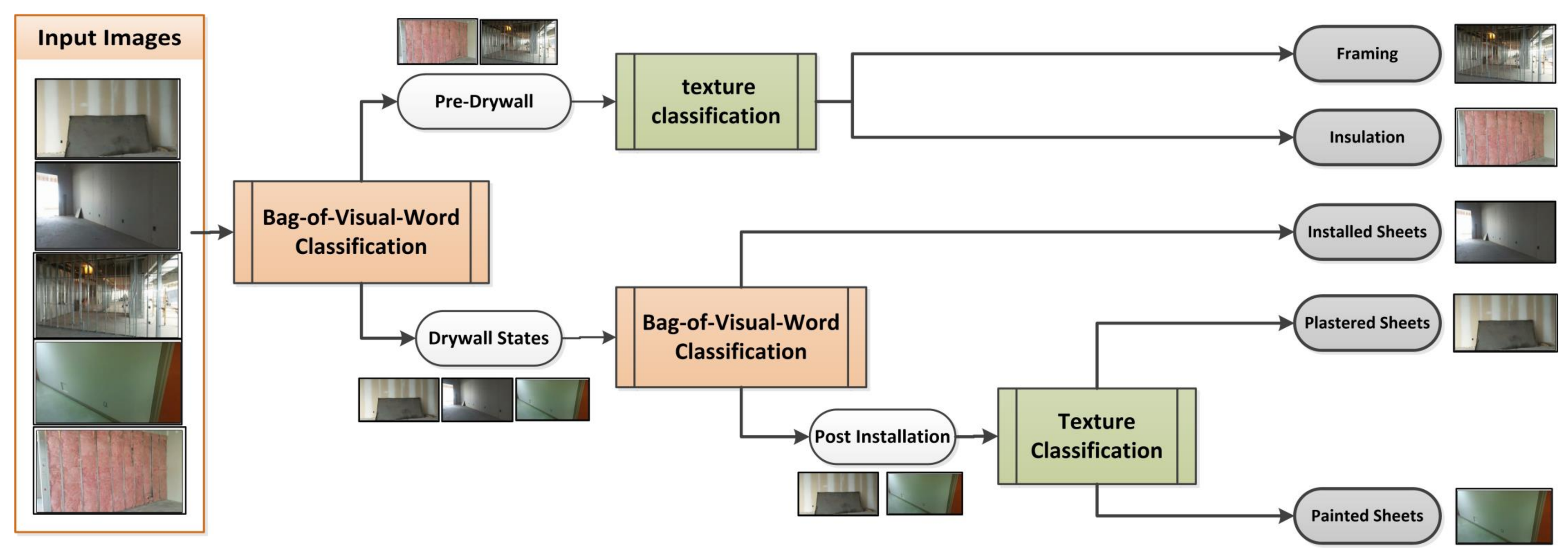
Data Collection

- Few construction sites were visited, and 750 color images (1920x1080 pixels) were captured using a smartphone.
- Images were captured at various illumination conditions, and they contain occlusion and high clutter (inherent to construction scenes).

State	Framing	Insulation	Installed Drywall	Plastered Drywall	Painted Drywall
number	150	150	150	150	150

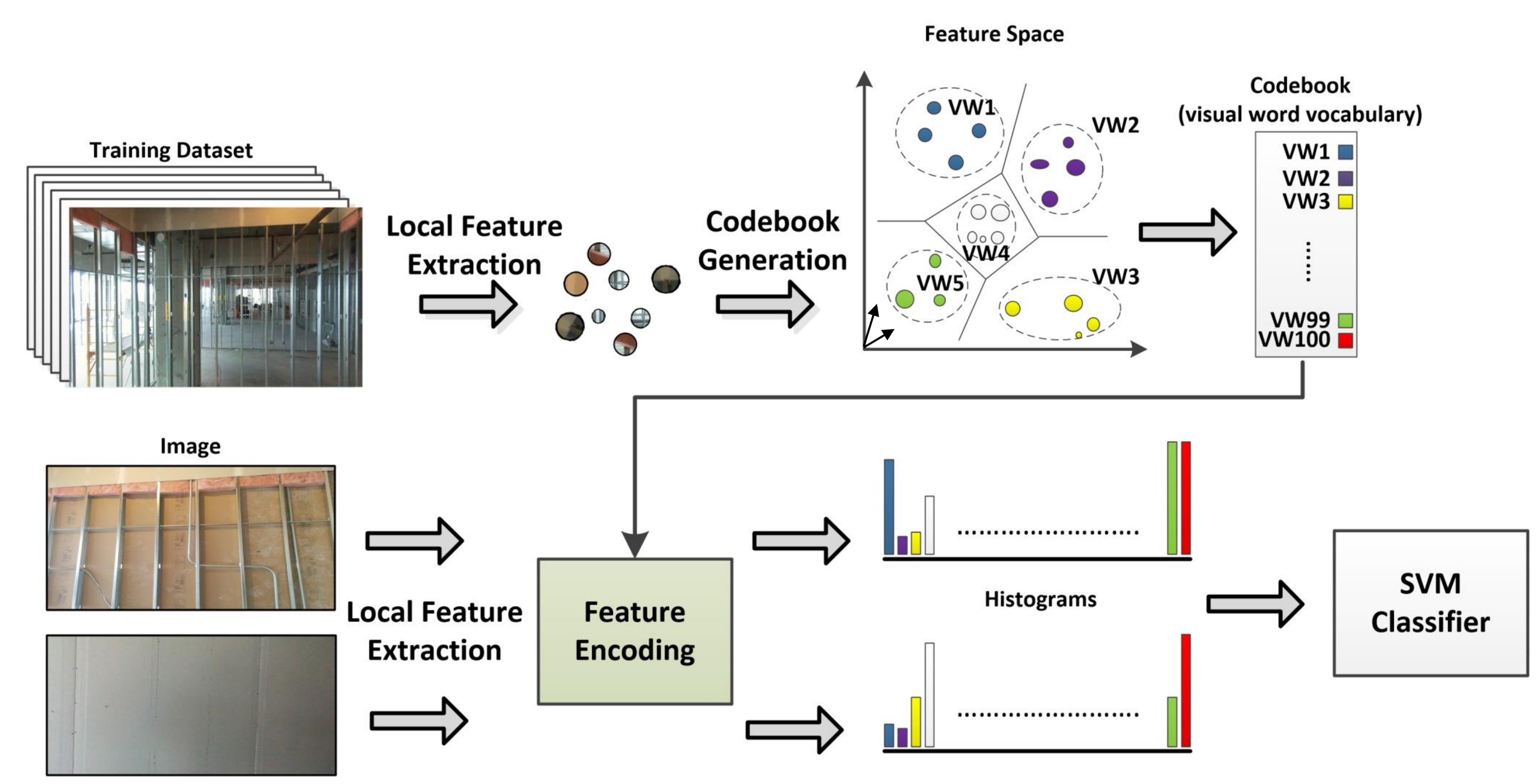
Automated Progress Detection

In this work, a combination of bag-of-visual-word (BOVW) and texture classification techniques are employed in a cascade scheme.



Features

- K-means clustering is performed on SURF features of images in the training set to create a visual codebook. Images are encoded using the codebook to generate feature histograms.
- Local binary pattern (LBP) histograms were used as feature for drywall texture classification (plastered/painted classification).
- The A* color channel (of LAB color space) and LBP histograms were used as features for insulation classification.



Model

- In this work, support vector machine (SVM) classifiers are used for classifying both codebooks and LBP histograms (linear kernel).

Results

The proposed algorithm was trained on 60% of the data and tested on the remainder 40%. These variations of the method were tested:

M1-BOVW for a 5-class classification problem (single step)
M2-Cascade scheme (BOVW using SURF features+ texture classification)
M3-Cascade (BOVW using dense SURF extraction+ texture classification)
The third method achieved the best result (see the confusion matrix).

Confusion matrix for best performing method
S1: Framing,…..,S5: Painted

	S1	S2	S3	S4	S5
S1	**95%**		5%		
S2	2%	**96%**	2%		
S3	1%		**97%**	2%	
S4				**95%**	5%
S5				4%	**96%**

Performance comparison for variations of proposed method

Method variation	Avg. Accuracy(%)
M1	73%
M2	82%
M3	96%

Discussion

The use of a cascade scheme (breaking the multi-class problem into a series of binary ones) and employing texture features for a few states increased the average accuracy by 23%. As expected, the images of the last two stages did not provide distinctive local features for a BOVW model. Painted and plastered sheets differ mostly in terms of patterns caused by plaster. This encourages the use of texture-based methods. The insulation/framing binary classification cannot be effectively achieved using BOVW because of the highly similar histograms of these two states (a huge portion of objects exist in both scenes). Compared to existing works, this solution achieves a 15% higher accuracy rate, and it is less sensitive to occlusion, varying illumination, and clutter.

Future Work

- Future work needs to be directed on the use of other local and derived features (such as the response to Sobel kernel, useful for last two stages).
- The classification of half states (e.g., half plastered/painted).
- Evaluation of the method in terms of time performance and adjustments for achieving real-time applications.

References

[1] C. Kropp, Ch. Koch, and M. König. Drywall state detection in image data for automatic indoor progress monitoring. *International Conference on Computing in Civil and Building Eng*. 2014.

[2] H. Hamledari, B. McCabe, and S. Davari. Automated computer vision-based detection of components of indoor under-construction partitions. Autom. in Construction 74: p 78-84. 2017