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Classification of major construction materials in construction environments using ensemble classifiers

Hyojoo Son [a], Changmin Kim [a], Nahyae Hwang [a], Changwan Kim [a,*], Youngcheol Kang [b]

[a] Department of Architectural Engineering, Chung-Aug University, Seoul 156-756, Republic of Korea
[b] OHL School of Construction, Florida International University, Miami, FL 33174, USA

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ABSTRACT

The automatic detection of construction materials in images acquired on a construction site has been regarded as a critical topic. Recently, several data mining techniques have been used as a way to solve the problem of detecting construction materials. These studies have applied single classifiers to detect construction materials—and distinguish them from the background—by using color as a feature. Recent studies suggest that combining multiple classifiers (into what is called a heterogeneous ensemble classifier) would show better performance than using a single classifier. However, the performance of ensemble classifiers in construction material detection is not fully understood. In this study, we investigated the performance of six single classifiers and potential ensemble classifiers on three data sets: one each for concrete, steel, and wood. A heterogeneous voting-based ensemble classifier was created by selecting base classifiers which are diverse and accurate; their prediction probabilities for each target class were averaged to yield a final decision for that class. In comparison with the single classifiers, the ensemble classifiers performed better in the three data sets overall. This suggests that it is better to use an ensemble classifier to enhance the detection of construction materials in images acquired on a construction site.

1. Introduction

The automatic detection of construction materials in images acquired on a construction site is essential for a wide range of construction applications, from the generation of a 3D as-built model to progress monitoring (see, for example, [1–5]). With the rapid deployment of image sensors on construction sites, images containing valuable project information are readily available. However, material detection in construction images is non-trivial and difficult. Construction materials in construction images may appear cluttered, occluded, or articulated, and the shapes and positions of construction materials are unpredictable.

Color has been recognized as an efficient feature for distinction of a material of interest from the background. Color has obvious advantages over other features such as texture and shape, especially in complex environments, as it is independent of the shapes and positions of the objects [6–8]. In addition, it is simple and computationally efficient to implement because it requires only the color values of each pixel in an image. It is therefore expected that material detection using color would be more robust and accurate and would overcome problems associated with construction environments compared to other features such as texture and shape.

In past research, color distribution has been used in efforts to detect construction materials in images acquired on a construction site. Neto et al. [9] proposed a method that employs edge detection and color to identify construction materials in images. In their approach, an edge detector algorithm detects edge pixels that belong to construction materials by comparing the RGB values in such pixels with the predetermined RGB values of the construction materials. After the edges have been detected, it groups the interior pixels to each set of edge pixels as an object. At the end of the operation, both of the resulting linked lists (the one for edges and the one for internal pixels) are stored under an object name. Zou and Kim [10] suggested a color-based method for identification of hydraulic excavators on a construction site. They use the hue feature to separate hydraulic excavators of different colors, and the saturation feature to differentiate each excavator of interest from its background, which consists of dark-colored soil and white snow. Simple thresholding methods using the hue and saturation features in conjunction with a method of calculating object centroid coordinates enable their system to produce accurate determinations of excavator idle time and working rate. The changing centroid coordinates of an excavator in successive images taken at constant time intervals are used as indicators of movement. Son and Kim [11] proposed an automated structural component recognition method that employs color and 3D data acquired from a stereo vision system for use in construction progress monitoring. The data

* Corresponding author. Tel.: +82 2 820 5726; fax: +82 2 812 4150.
E-mail address: changwan@cau.ac.kr (C. Kim).

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processing first relies on color features to effectively extract information on structural components by employing color invariance, 2D object segmentation, and two-stage post-processing of removing unnecessary noise unrelated to the structure of interest and supplementing the image with information that may have been unintentionally eliminated. That information is then utilized to extract 3D coordinates for each color feature. The color image is used to guide the detection of features, while the 3D data are used to compensate for the pose of the feature.

In recent years, data mining methods such as artificial neural networks (ANNs), Gaussian mixture models (GMMs), and support vector machines (SVMs) have been investigated as a way to detect construction materials in images by use of a color model. Zhu and Brilakis [12] applied ANNs to classify regions of concrete in images acquired on a construction site. The images were first divided into regions through image segmentation using color. Then the color and texture features of each region were calculated, and the regions were classified using a pre-trained ANNs classifier. Son et al. [5] performed a comparative analysis of three data mining algorithms (GMMs, ANNs, and SVMs) for detection of concrete regions in images acquired on construction sites. The results show that the accuracy of the SVM they employed is better than that of the GMM or the ANN in dealing with concrete detection.

In previous studies, single classifiers have been employed to detect construction materials—and distinguish them from the background—by using color as a feature. However, a single classifier might not produce the optimal result in construction environments in which the color of one construction material is similar to that of others around it, or the inherent color property of a construction material is altered because of the effects of variation in illumination. For these reasons, the detection of construction materials still remains a challenging problem and there is still room for further improvement of detection performance. In order to solve such complex classification problems, heterogeneous ensemble classifiers (combined into a so-called multiple classifier system) have been proposed and they have been shown to be considerably successful in highly complex domains compared to ones with individual classifiers [13–17].

An ensemble classifier is comprised of a set of individual classifiers whose predictions are combined to obtain a highly accurate classification. Systems of this type have been proposed as a way to achieve better classification performance than with a single classifier [15,17] and are expected to reduce the variance in the estimation errors made by the individual classifiers [18,19]. The effectiveness of ensemble classifiers for detection of materials in complex environments has been demonstrated in various fields (see, for example, [20–24]). To the knowledge of the authors, the applicability of ensemble classifiers to the detection of construction materials has not been explored thus far.

The aim of this study was to improve the accuracy of detection of major construction materials such as concrete, steel, and wood by using ensemble classifiers. It was hypothesized that ensemble classifiers achieve higher accuracy than single classifiers in detecting construction materials in construction environments. This belief is based on the general expectation that ensemble classifiers can outperform individual classifiers [17]. The rest of the paper is organized as follows. Section 2 describes data collection and pre-processing. Section 3 describes the methods employed by the single classifiers and the scheme employed in the proposed ensemble classifier. In Section 4, the results of experiments on the performance of the proposed ensemble classifier are compared with that of single classifiers in terms of average prediction accuracy. Finally, the conclusions are presented in Section 5.

2. Data collection and data pre-processing

2.1. Data collection

Without a comprehensive data set, it cannot be concluded that an ensemble classifier yields better accuracy than single classifiers in detecting construction materials in construction environment. Because comprehensive data sets for construction material detection were not readily available, a total of three data sets (one each for concrete, steel, and wood) were generated.

The appearance of a construction material's surface colors can be affected by environmental factors such as changes in the direction and intensity of illumination. Since most construction sites are outdoors, the intensity of illumination varies unpredictably and uncontrollably, depending on the time of day, seasonal variations, and weather conditions (sunny, cloudy, or foggy), thereby resulting in large variations in the appearance of a construction material's surface colors. To account for such variations, 108 photographs were taken at a total of 50 construction sites for concrete detection, 91 photographs were taken at a total of 80 construction sites for steel detection, and 50 photographs were taken at a total of 14 construction sites for wood detection. Fig. 1(a), (c), and (e) present examples of construction site images for concrete, steel, and wood detection. Digital cameras with resolutions ranging from 3 megapixels to 12 megapixels were used when collecting data. The photographs were intended to contain either of the three structural components (concrete, steel, and wood) in images of actual construction-site scenes in order to validate the effectiveness and robustness of the proposed method for use in applications such as the generation of 3D as-built models and progress monitoring. Therefore, the photographs were taken at a distance from structures so that images contained the entire structures.

Each photograph was then divided into sub-regions of either 25×25 pixels or 50×50 pixels. Each sub-region was categorized and labeled as either a material of interest or the background, or as unable to say whether the sub-region was the material of interest or the background. Fig. 1(b), (d), and (f) display examples of the sub-regions for concrete, steel, and wood data sets. For example, the first, second, and third rows in Fig. 1(b) show the examples of sub-regions that were labeled as the concrete, the background, and unable to say whether the sub-region was the concrete or the background. Of the sub-regions, 48.2% from the concrete data set, 22.8% from the steel data set, and 49.0% from the wood data set were categorized as unable to say whether the sub-region was the material of interest or the background. These sub-regions were then excluded from the data set. As a result, every data set consisted of material or non-material pixels. The former are pixels associated with objects made of materials such as concrete, steel, and wood, while the latter are pixels related to the background. To assess whether the heterogeneous ensemble classifiers perform better than single classifiers, this study made a particular effort to collect and include as many materials as possible with color properties similar to those of the materials of interest. In each data set, the background included all kinds of scenery—bricks, construction equipment, fences, forms, pipes, safety nets, the sky, soil, traffic signs, trees, windows, and other construction-related materials. For example, the background of the concrete data set included objects made of materials such as steel and wood in order to evaluate results in the presence of different construction materials.

In total, the data collected from the concrete, steel, and wood sub-regions and their background sub-regions amounted to over 113 million pixels for concrete detection, 95 million pixels for steel detection, and 35 million pixels for wood detection. The first data set contained approximately 44 million pixels of concrete and 69 million pixels of background. The second data set consisted of