Automated On-site Retrieval of Project Information

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Abstract. Among several others, the on-site inspection process is mainly concerned with finding the right design and specifications information needed to inspect each newly constructed segment or element. While inspecting steel erection, for example, inspectors need to locate the right drawings for each member and the corresponding specifications sections that describe the allowable deviations in placement among others. These information seeking tasks are highly monotonous, time consuming and often erroneous, due to the high similarity of drawings and constructed elements and the abundance of information involved which can confuse the inspector. To address this problem, this paper presents the first steps of research that is investigating the requirements of an automated computer vision-based approach to automatically identify "as-built" information and use it to retrieve "as-designed" project information for field construction, inspection, and maintenance tasks. Under this approach, a visual pattern recognition model was developed that aims to allow automatic identification of construction entities and materials visible in the camera's field of view at a given time and location, and automatic retrieval of relevant design and specifications information.

1 Introduction

Field construction tasks like inspection, progress monitoring and others require access to a wealth of project information (visual and textual). Currently, site engineers, inspectors and other site personnel, while working on construction sites, have to spend a lot of time in manually searching piles of papers, documents and drawings to access the information needed for important decision-making tasks. For example, when a site engineer tries to determine the sequence and method of assembling a steel structure, information on the location of each steel member in the drawings must be collected, as well as the nuts and bolts needed for each placement. The tolerances must be reviewed to determine whether special instructions and techniques must be used (i.e. for strict tolerance limits) and the schedule must be consulted to determine the expected productivity and potential conflicts with other activities (e.g. for crane usage).

All this information is usually scattered in different sources and often conflicts with expectations or other information, which makes the urgency and competency of retrieving all the relevant textual, visual or database-structured data even more important. However, manual searches for relevant information is a monotonous, time-consuming process, while manual classification [1] that really helps speed up the

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search process only transfers that problem to the earlier stage. As a possible alternative to user-based retrieval, this paper builds on previous modeling, virtual design and collaboration research efforts (i.e. [2]) and presents a computer vision type approach that, instead of requiring browsing through detailed drawings and other paper based media, it can automatically retrieve design, specifications and schedule information based on the camera's field of view and allow engineers to directly interact with it in digital format.

The computer vision perspective of this approach is based on a multi-feature retrieval framework that the author has previously developed [3]. This framework consists of complementary techniques that can recognize construction materials [4; 5] and shapes [6] that, when augmented with temporal and/or spatial information, can provide a robust recognition mechanism for construction-related objects on-site. For example, automatically detecting at a certain date and time (temporal) that a linear horizontal element (shape) made out of red-painted steel (material) is located on the south east section of the site (location) is in most cases sufficient information to narrow down the possible objects matching such description to a small and easily manageable number.

This paper initially presents previous work of the author that serves as the base for the computer vision perspective of this research and continues with the overall approach that was designed and the relationship between its various components. Conclusions and future work are then presented. At this stage, it is important to note that this work is a collaboration effort with the National Institute of Standards and Technology (NIST) in steel structure inspection, and therefore, all case studies and examples are focused on steel erection.

2 Previous Work

The following two sub-sections present the findings of recent research efforts of the author in construction site image classification based on the automatic recognition of materials and shapes within the image content [3; 4; 5; 6], which is the basis for the proposed on-site project information retrieval approach that will be presented in the following sections. The purpose is to familiarize the reader with some of the main concepts used in the mechanics of this research.

2.1 Recognition of Construction Materials

The objective of this research [4; 6] was to devise methods for automating the search and retrieval of construction site related images. Traditional approaches were based on manual classification of images which, considering the increasing volume of pictures in construction and the usually large number of objects within the image content, is a time-consuming and tedious task, frequently avoided by site engineers. To solve this problem, the author investigated [7] using Content Based Image Retrieval (CBIR) tools [8; 9; 10] from the fields of Image and Video Processing [11] and Computer Vision [12]. The main concept of these tools is that entire images are matched with other images based on their features (i.e. color, texture, structure, etc). This investigation revealed that CBIR was not directly applicable to this problem and had to be redesigned and modified in order to take advantage of the construction domain characteristics. These modifications were based on the need for:

1) Matching parts of each image instead of the entire content. In most construction site images, only a part of each picture is related to the domain while the remaining parts are redundant, misleading and can possibly reduce the quality of the results. For this purpose, it was necessary to effectively crop the picture in order to isolate construction-related items (pavement, concrete, steel, etc.) from picture background (sky, clouds, sun, etc.) or foreground (trees, birds, butterflies, cars, etc.).

2) Comparing images based on construction-related content. Each relevant part of the picture needs to be identified with construction-related terms. The comparison of images with other images or with objects in a model based system should not be performed at a low level (using color, texture, etc.). Instead, the comparison could be based on features such as construction materials, objects and other attributes that site engineers are more familiar with.

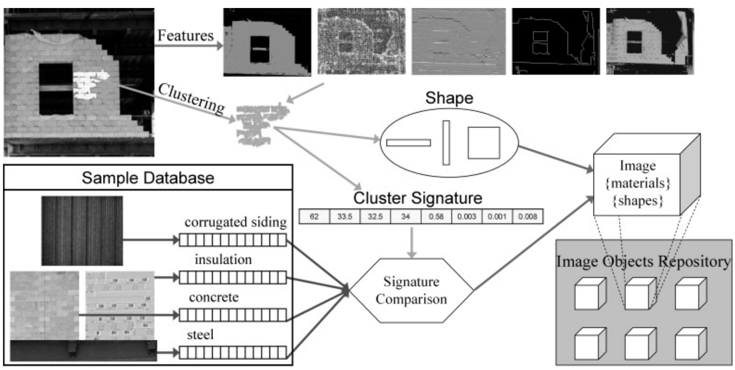

Fig. 1. Construction Materials and Shapes Recognition [6]

Overall, this material-based classification method is comprised of 4 steps (Fig. 1). In the first step, each image is decomposed into its basic features (color, texture, structure, etc.) by applying a series of filters through averaging, convolution and other techniques. The image is then cropped into regions using clustering and the feature signatures of each cluster are computed. During the fourth step, the meaningful image clusters are identified and isolated by comparing each cluster signature with the feature signatures of materials in a database of material image samples called “knowledge base”. The extracted information (construction materials found) are then used to classify each image accordingly. This method was tested on a collection of more than a thousand images from several projects. The results showed that images can be successfully classified according to the construction materials visible within the image content.

2.2 Recognition of Construction Shapes

The objective of this research [6] was to enhance the performance of the previously presented material-based image classification approach by adding the capability of recognizing construction shapes and, by cross-referencing shape and material information, detect construction objects, such as steel columns and beams. This information (materials and shapes) was then integrated with temporal and spatial information in a flexible, multi-feature classification and retrieval framework for construction site images [3].

The motivation behind the need for more flexibility was that several materials are frequently encountered in construction site images (e.g. concrete, steel, etc.) and, unless accurate spatial and temporal information are also available, image retrieval based on such materials could retrieve an overwhelming amount of pictures. In such circumstances, it is necessary to classify images in even smaller, more detailed groups based on additional characteristics that can be automatically recognized from the image content. Earth, for example, can be classified into the several different types of soil [13] while concrete and steel objects can be classified according to their shape (columns, beams, walls, etc.). The latter is what this shape recognition approach can successfully recognize. In this work, shape is represented as the dimensions of each material region and is stored as an additional feature in the multi-feature vector used to mathematically describe each material.

This approach operates by skeletonizing construction objects if such a skeleton exists. Objects in this case are presumed to be image areas of similar characteristics (e.g. similar color distribution, similar texture, or similar structure) with a certain degree of uniformity (since construction materials are often characterized by consistent colors, textures and structures). These image areas are selected using a flooding-based clustering algorithm [5] with high accuracy, and the materials that comprise each cluster (group of pixels) are identified.

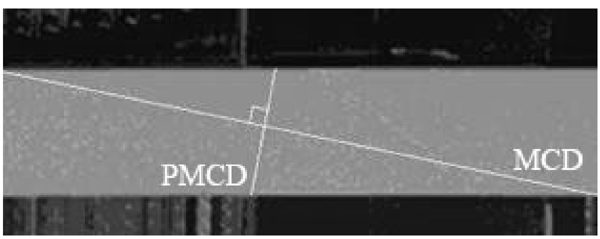

Fig. 2. Steel cluster and measurements [6]

The linearity and (if linear) orientation of the “object’s spine” of each cluster is evaluated. Both are determined by computing the maximum cluster dimension (MCD) and the maximum dimension along the perpendicular axis of MCD (PMCD) (Fig. 2). These dimensions are then used to determine the linearity and orientation under three assumptions (i) If MCD is significantly larger than PMCD, then the object is linear, (ii) If the object is linear, then the tangent of the MCD edge points represents its direction on the image plane; the object’s “spine”, (iii) If the computed direction is within 45 degrees from the vertical/horizontal image axis then the linear object is a column/beam, respectively. This method was tested on the same collection of more than a thousand images from several projects. The results showed that images can be successfully classified according to the construction shapes visible within the image content.

3 On-site, Vision-Based Information Retrieval Model

The primary goal of this research is to minimize the time needed for on-site search and retrieval of project information, and by consequence, to reduce cost and effort needed for this process. In order to achieve this objective, the author investigated the requirements of a vision-based approach that focuses on automatically retrieving relevant project information to the user for on-site decision-making in construction, inspection, and maintenance tasks. Figure 3 summarizes the mechanics of the novel information retrieval model:

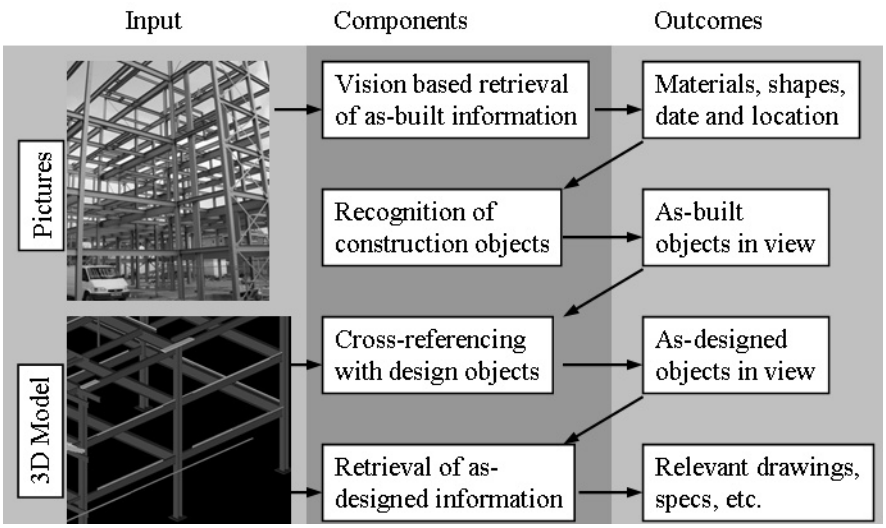

Fig. 3. On-site Information Retrieval Model

3.1 Retrieval of as-built Information and Objects Recognition

This component aims to detect all possible construction-related visual characteristics within the image content, such as surface materials and object shapes, and the relative position of each in reference to the image plane. This information is extracted using the materials and shapes detection tools described above [4, 6]. The input in this case is construction site time/location/orientation-stamped photographs (using a GPS digital camera), and a set of user-pre-selected material image samples needed for the vision algorithms involved to understand what each material looks like [4]. The image components (red, green, blue and alpha [transparency info]) are initially separated for further analysis. Image and video processing filters then extract the normalized color distribution and color histograms, the texture response of each frame to sets of texture kernels, the wavelet coefficients (when wavelets are used) and other mathematical image representations. The values of these representations are then grouped by image areas (clusters) that contain the same materials, and compacted into cluster signatures using statistical measures such as mean, mode, variance, etc. The signature of each cluster is then compared with those of the pre-classified material samples so as to detect their existence within the image content. The outcome is material and shape information grouped in vectors (signatures, Fig. 4) by relative position in reference to the image plane, along with the hardware provided time, location and orientation data.

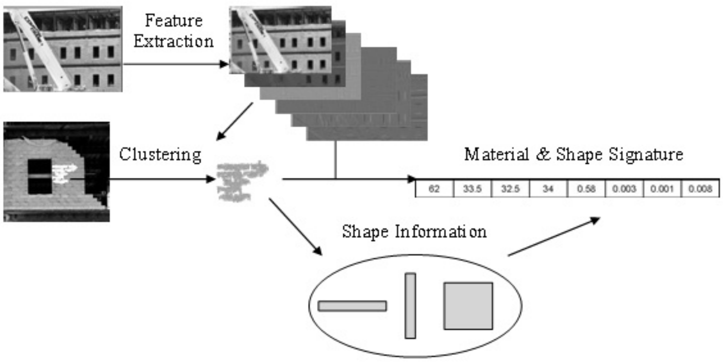

Fig. 4. Materials/Shapes Recognition – Representation with Image Signatures

The as-built objects are then recognized based on Euclidian distance matching. Each attribute (texture response, shape directionality, etc) in the multi-dimensional material and shape signature represents a different dimension of comparison. By comparing the distance of each attribute of the extracted signatures with the corresponding attributes of the object types in the 3D CAD model, the similarity of each signature with each object type in the model can be represented mathematically. The design object type with the highest similarity (least distance) is then selected to represent the recognized object.

3.2 Cross-Referencing Detected Objects with Design Objects and Retrieving Design Information

The position where the camera was located on the site and the direction in which it was facing are useful in narrowing down the possible construction objects that might match the detected object and its material and shape information [3]. This is where off-the-shelf GPS cameras can be really useful since the location and orientation information that they provide is enough to determine the camera's line-of-sight and the corresponding viewing frustum. This information, along with a camera coordinate system that is calibrated with the coordinate system used in creating the design of the constructed facility, can then assist in more accurately matching with the design objects that are expected to be in the camera's view. Calibration is essential in this case, since CAD designs typically use a local coordinate system.

In this approach, the object attributes are enhanced with camera position and orientation information and a Euclidian distance matching is repeated. The difference in this step is that specific objects are sought instead of generic object types. For example, while any steel beam is sufficient to determine the type of an as-built steel beam object in the previous step, the specific steel beam that it corresponds to in the design model is needed in this case. The CAD models used for these comparisons were based on the CIS/2 standard that provides data structures for multiple levels of detail ranging from frames and assemblies to nuts and bolts in the structural steel domain (Fig. 5). The CIS/2 standard is a very effective modeling standard and was successfully deployed on a mobile computing system at NIST [14].

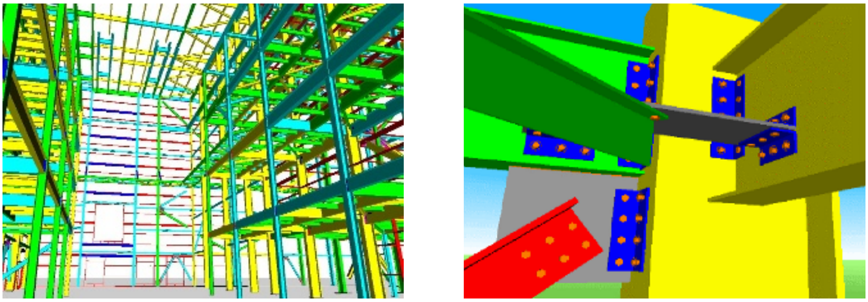

Fig. 5. CIS/2 product models: (left) Structural frame of large, multistory building and (right) Connection details with bolts [14]

After minimizing the number of possible matches, the next step is to provide the user with the relevant design information needed. In this case, the information related to each possible match is acquired from the model objects and isolated. This way, the user need only browse through small subsets of information (i.e. a few drawings, a few specification entries, a segment of the schedule, etc.).

4 Conclusions

Designing and implementing a pattern recognition model that allows the identification of construction entities and materials visible in a camera's field of view at a given time was the base for this ongoing research work. The long-term goal is to reduce the cost and effort currently needed for search and retrieval of project information by using the automatically detected visual characteristics of project-related items to determine the possibly relevant information that the user needs. Thus, the innovative aspects of this research lie in the ability to automatically identify and retrieve project information that is of importance for decision-making in inspection and other on-site tasks and, to achieve this, a new methodology that can allow rapid identification of construction objects and subsequent retrieval of relevant project information for field construction, inspection, and maintenance was developed. The merit of its technical approach lies in taking advantage of the latest developments in construction material and object recognition to provide site personnel with automated access to both as-built and as-designed project information. Automated retrieval of information can also, for example, serve as an alerting mechanism that can compare the as-built and as-designed information and notify the site (or office) personnel of any significant deviations, like activities behind schedule and materials not meeting the specifications. Reducing the human-intervention from this tedious and time-consuming process is also expected to reduce man-made mistakes. Eventually, it is anticipated that the designed model will allow construction personnel to increase their productivity in field tasks such as inspection and maintenance, thereby achieving cost and time savings and lesser life cycle costs in constructed facilities.

5 Ongoing and Future Work

The presented model will be validated in 2 stages. The purpose behind the first stage of testing is to explore the limits of the materials and shape recognition algorithms in detecting installed members and cross-referencing them with their design information. A case study is planned to be conducted at the NIST structural steelwork test bed in Gaithersburg, MD. Based on a CIS/2 model for a multistory steel frame that was erected with many errors, several experiments will be designed to evaluate the ability of the designed prototype to identify, extract, and present relevant information to an inspector attempting to detect errors and irregularities in the structure. Based on the observed performance, one can check whether this situation is better than situations wherein the relevant information was manually identified and recovered. The second stage of testing will be done in collaboration with industrial partners on real projects. This includes retrieval of design information and instructions to serve as an assembly aid as well as design retrieval for evaluating compliance with specifications.

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