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Image analysis and automatic composition of ceramic mosaics[1]

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1 Introduction

In many different industrial fields, computer vision and robotics are jointly employed to perform repetitive, high-speed tasks, for quality inspection, to automatically move goods, and so on. This paper presents a hybrid computer vision-robotics system for the automatic creation of ceramic mosaics, i.e. reproductions of patterns, synthetic geometries, or, in general, images, by means of ceramic tiles (Fig. 3.1). This task is currently performed, in most cases, by an expert, that is, however, slow and prone to errors. The system under development should be able to create mosaics at a higher speed and with the precision typical of computer-based systems. Several working hypotheses can be made:

1. tiles can have different orientations in the pick-up position;
2. tiles can have different orientations in the place position;
3. tiles can be upside-down in the pick-up position;
4. tiles can have different shapes/sizes;
5. tiles can be uniformly colored or textured;

Each of these hypotheses introduces complexity in the system. The current, preliminary version of the system accounts only for hypothesis #1, and we plan to consider also #2. The remaining three hypotheses will be considered as a topic of future research.

2 Related works

In this section, we present a brief overview of the most relevant works addressing the subproblems that need to be dealt with to produce a complete system for the automatic composition of ceramic mosaics.

Mosaic rendering. Mosaic rendering refers to the problem of tesselating a source digital image in order to reproduce it in a mosaic-like style. A very simple way to achieve tesselation is by reducing the spatial resolution, but the resulting appearence is very different from that of traditional mosaics. Many digital mosaic techniques have been proposed by the computer graphics community and recently surveyed by Battiato *et al.* in [2]. However, these approaches do not aim to produce real ceramic mosaics, but only virtual mosaics. Thus, a large class of approaches are not applicable to our framework. Among the methods preserving the tile geometry, we recall Hausner's algorithm [5]. Fixed-size, fixed-shape tiles are adapted to the image contours by means of Voronoi diagrams. Even though this approach is interesting, in this preliminary phase we are bounded to a regular structure in the final placement of the tiles, i.e. with a fixed orientation.

Color mapping. In mosaic rendering techniques the color problem seems to be of little account. Each tile is simply colored either by a sample color or by an average color of the image

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portion covered by the tile. On the other hand, in our application, we have strong constraints on the color of the available tiles. In the literature, the process of assigning to each pixel the optimal color is usually divided in two steps: “quantization” and “dithering”. Quantization [6] aims at diminishing the number of colors, while dithering reduces the visibility of quantization errors, so that combinations of available colors reproduce non-available colors [1]. An important class of dithering methods originates from Floyd and Steinberg’s error-diffusion algorithm [4].

Image segmentation. Image segmentation is necessary in order to detect the position and orientation of the tiles to be picked by the robotic system. Approaches to image segmentation can be divided in four classes: thresholding methods, edge-based methods, region-based methods, and active contours methods. Thresholding methods [11] label pixels as background or foreground by locally evaluating the pixel color. Therefore, these methods give better results when background and foreground are well separated in the chosen color space. Edge-based methods [13] exploit edge detection, but require well defined images. Region-based methods [9] split and merge regions of the image according to color similarity. Finally, active contours methods [10] iteratively adapt an initial shape in order to minimize suitable energy functions.

Visual servoing. A system where a robot uses visual information to control its end-effector’s configuration (i.e. position and orientation) is said to be visual-servoing [7]. In these systems the visual information is obtained by a camera, either placed on the end-effector [12] or fixed in the robot work space. In the first case, the robot has more visibility than in the second case, but calibration problems are greater. As for control architectures, two main approaches can be adopted according to the use of visual information in the control loop. In position-based control [8] the robot takes its end-effector to a certain target configuration, whereas in image-based control [3] the robot task is to reach a configuration such that the image acquired by the camera corresponds to a certain target image.

3 Description of the System

The system is composed of two sub-modules: one consisting of computer vision algorithms to render the mosaic and to analyze live images to extract position and orientation of the ceramic tiles, and one devoted to control the robot for the pick-and-place of the tiles. The scheme of the overall architecture is reported in Fig. 3.2. The overall mosaic is split into square 12×12 sub-mosaics which are composed by the robot row by row. When a row is completed, it is removed and assembled with the rest of the composition. A tray containing a set of ceramic tiles that can be used by the robot for composing the mosaic is available. A color camera (Pixelink PL-A742) acquires an image I which is elaborated to extract features regarding the color, the position and the orientation of the available tiles. This information is then forwarded to the robotic sub-module to be used to calculate the trajectory that robot has to follow to pick the required tile and to place it in the right place in the row. A counter is used to keep track of the next required tile.

The *computer vision sub-module* is described in Fig. 3.3. The image I_{ref} is decomposed into a set of colors, depending on the used tile size, the size of the mosaic, and the dimensions of I_{ref}. Current implementation of mosaic rendering employs a simple tesselation technique that divides the image in a fixed number of rows and columns of the same size (Fig. 3.4(a)). The color mapping is achieved by averaging the result of the convolution with a Gaussian filter.

This set of colors is then parsed in order by means of the counter that drives the simultaneous advance of the two sub-modules (see Fig. 3.2). Once the next target is characterized, image segmentation algorithms extract the ceramic tiles, their color features, and their position and orientation from the live camera. Image segmentation is achieved by converting the image I in the HSV color space and thresholding the V component. In fact, the tray is equipped with a dark background, allowing a fast and simple segmentation (Fig. 3.4(b)). This is prone to errors when black tiles are inserted on the tray, thus pattern analysis techniques are under development in order to exploit texture in the segmentation of the image.

The best candidate for the next pick, given the characteristics of the next target, is identified and its position and orientation are forwarded to the robotic sub-module in order to allow the robot to pick the correct tile from the tray and to place it into the target position in the row.

In Fig. 3.5 a schematic representation of the *robotic sub-module* is reported. The Cartesian coordinates received from the vision sub-module are used to plan the optimal trajectory that drives the end-effector in the proximity of the required tile which is picked using a simple gripper. The set of target configurations where the tiles have to be placed can be computed offline by considering the fact that they are always disposed in a row. The output of the counter can be used to recover the target configuration where the current tile has to be placed. Thus, another optimal trajectory that drives the end-effector to the target position is planned and the tile is released in its corresponding slot. At this point the robot is ready for handling the next tile and the process starts over. A model of the robot is reported in Fig. 3.6.

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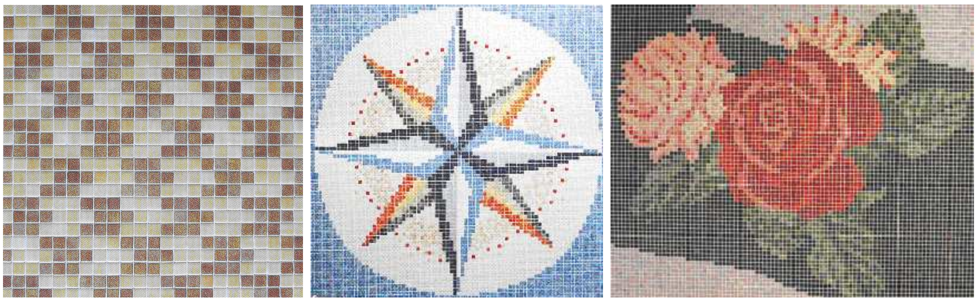


(a) Pattern (b) Synthetic geometry (c) Generic image

Figure 3.1: Examples of ceramic mosaics

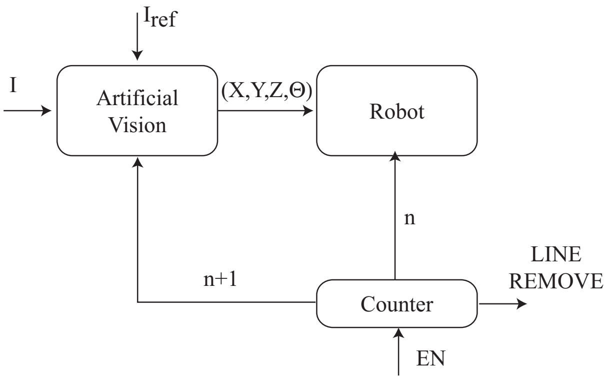


Figure 3.2: The overall architecture

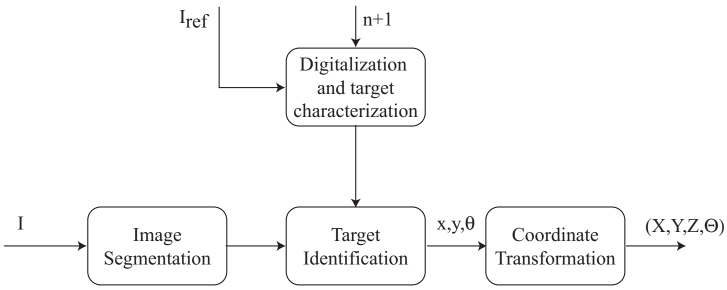
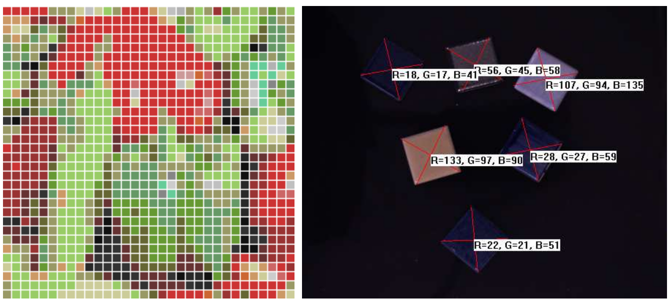


Figure 3.3: The computer vision sub-module



(a) Result of tesselation (b) Result of image segmentation

Figure 3.4: Some preliminary results of the computer vision module

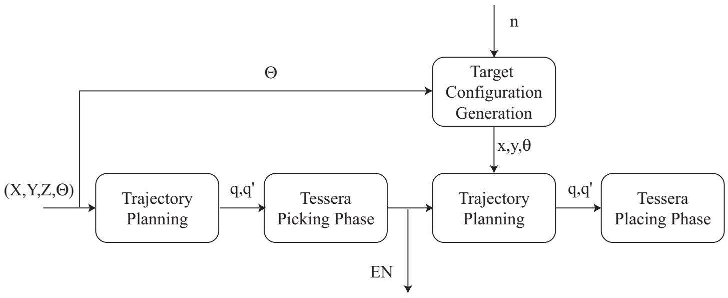


Figure 3.5: The robotic sub-module

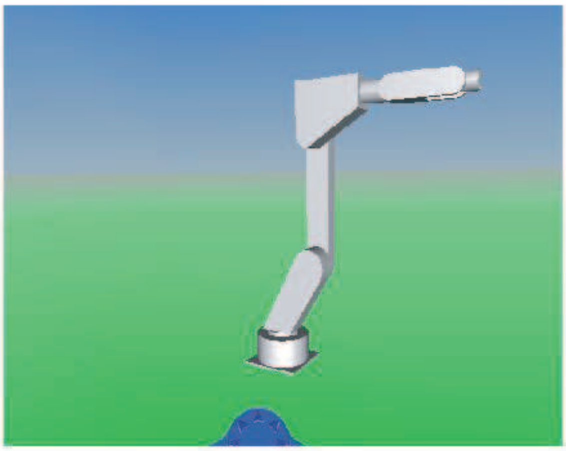


Figure 3.6: The virtual model of the robot