Continuous room localization using painting detection

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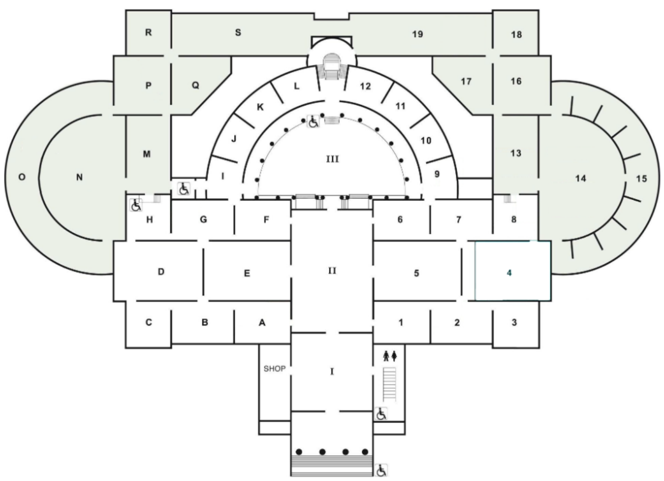

Fig. 1. A ground plan of The Museum of Fine Arts, Ghent.

***Abstract*—This paper describes our method to localize a painting on a ground plan based on The Museum of Fine Arts in Ghent.**

I. Introduction

This paper introduces a framework for rapid painting detection. _ToDo: What makes this work useful?

_ToDo: Why should someone spend time to read this paper

_ToDo: clarification of title and context
_ToDo: which problem has been solved
_ToDo: overview of related work
_ToDo: benefits and shortcomings of related work
_ToDo: overview of your own contributions This paper contains x contributions: _ToDo: overview of results
_ToDo: why these results are useful
_ToDo: overview of structure of the paper In section 2 ...
Based on a frame from a camera which contains a painting, Figure 1 shows the ground plan that is used to mark the correct room

II. Painting Detection

_ToDo: ook dingen uitleggen die niet werkte

- _ToDo: vanishing points
- _ToDo: hough transformatie
- _ToDo: lijn intersectie
- _ToDo: gabor filter
- _ToDo: local binary patterns

_ToDo: gebruik ook afbeeldingen

A. Painting Segmentation

The first step of the algorithm is the segmentation of an arbitrary video frame to detect a painting. A typical painting contains the art on its own enclosed by a painting frame. This painting frame causes a strong change in environment, increasing the effectiveness of an edge detector. Extracting the edges with the Canny edge detector yields a first indication of where a painting might be. If the full painting frame is visible on the video frame, its contour can be calculated using [1] which returns a vector of points for each contour. We consider only contours which have four points.

It is possible that multiple paintings exist on a single frame. However, the algorithm's goal is to detect in which room the user is located. Multiple paintings on the same wall belong to the same room. Hence, the algorithm will try the matching procedure in a later phase on one detected painting with the largest surface area. The remaining paintings are ignored but may be the result of the segmentation step in any of the following video frames.

The detected painting is then transformed through a homography to a rectified version which serves as the input of the following stage.

B. Feature Detection

C. Path Tracking

Once a painting is identified and matched, it can be localized on the ground plan. To achieve this, the ground plan is converted into a directed graph. The nodes of this graph are the rooms of the museum and the edges define the connections between rooms. When a user starts recording paintings, the matching algorithm will be performed on each frame and a location will be found. The graph is able to mark nodes in three distinct ways. A green node is the start of the path, an orange node is an intermediate path and the blue node is the end of the path. The path ends when the user stops recording. The path direction is also visualized by coloring the corresponding edges green. Note that when a cyclic path occurs which was walked in both directions, information of order is lost.

To illustrate the path tracking algorithm, a small segment consisting of rooms 1, 2, 3, 4, 5, 6, 7 and 8 are converted into such a graph and is show on figure 2.

D. Database

The database consists of 688 images of various paintings and sculptures in the museum. In this work we only focus on the paintings of this dataset. The paintings were extracted

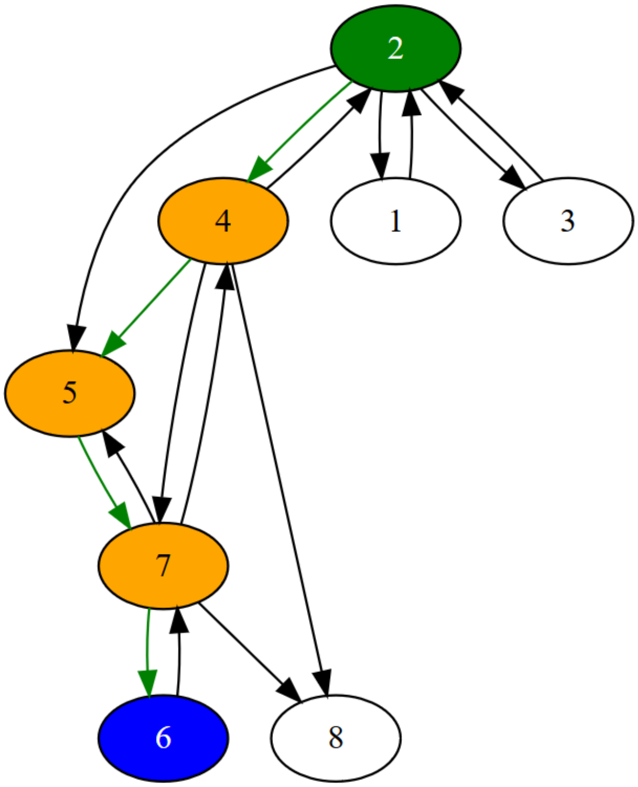

Fig. 2. Path tracking using a graph. The green marks the path's start, orange nodes the visited rooms, and blue the last one visited. Edges in green denote help visualize the path.

from two different camera's: a Nokia 7 plus and a Samsung A3. Each image also contains the room in which it resides as meta-data.

To reduce the load time of this database, a prebuilding stage was implemented. This stage reduces each image to a collection of interest points and corresponding descriptors for these interest points as generated by the ORB [2] algorithm.

III. Evaluation

To measure the performance metrics of our algorithm, we gather statistics from the three different parts of the method: painting segmentation, the matching algorithm and room localization. A random sample ($n = 30$) of the dataset was taken to evaluate our method.

To evaluate the painting segmentation algorithm, each image from the random sample must first be manually segmented. This manual segmentation results in 4 coordinates of a polygon which will be used as the ground truth and represent the ideal polygon. Afterwards, the segmentation is done automatically by the algortihm, which also gives four coordinates of a polygon. To illustrate, both polygons are shown on 3. To measure the similarity of these two polygons, we first calculate the intersection area A_i and the area of the red polygon A_r. The ratio of A_i to A_r describes the closeness of two polygons with 100% being a perfect match and 0% having no intersection at all. There is one case where this statistic does not work. When the red polygon is fully enclosed by the green

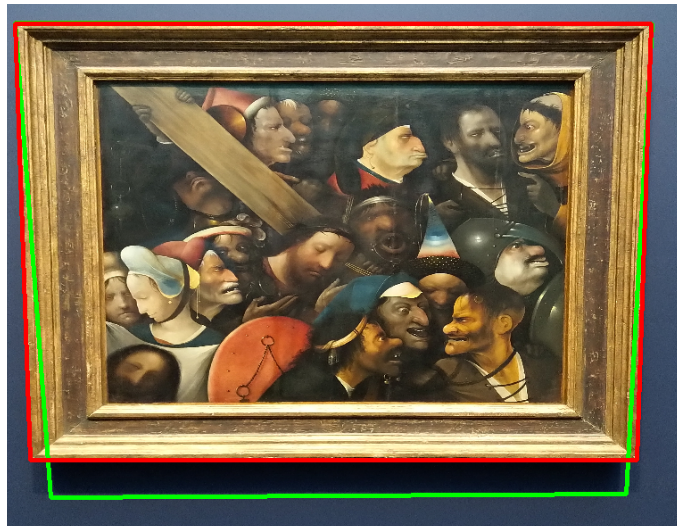

Fig. 3. A comparison of a manually selected polygon (red) and the polygon found by the segmentation algorithm (green).

polygon, A_i will be equal to A_r, resulting in a fake perfect match. To prevent this, the role of the green and red polygon are switched when this case occurs.

A next metric is

The matching algorithm has to be evaluated manually by comparing the matcher's result. The correctness of the matching algorithm is simply the ratio of the correct matches against the false matches.

To evaluate the room localization, a sample of the video dataset was taken. The generated path is compared against the actual path.

IV. Results

Painting segmentation: 88.57 % correct segmentation _ToDo: qualitative as well as quantitative

_ToDo: quantitative: graphs, tables, roc-curves, f1-scores, ...

_ToDo: qualititative: technisch, show where and why the method succeeds or fails, pictures of easy and difficulty cases

Because our method relies heavily on edge detection, there are cases where this could have a negative impact. In many cases, there is a shadow underneath the painting, as shown on figure 4.

V. Conclusion

_ToDo: overview of the most important contributions and the results, without introducing anything new

_ToDo: after the reader has read the paper, the reader can look at the contributions and results from a different viewpoint

_ToDo: statements can be made more explicit

_ToDo: eventueel future work

Fig. 4. An example of a shadow underneath the painting. This usually results in the segmentation algortihm to include this shadow as part of the painting because of the strong edge.

References

[1] S. Suzuki and K. be, "Topological structural analysis of digitized binary images by border following," *Computer Vision, Graphics, and Image Processing*, vol. 30, no. 1, pp. 32 – 46, 1985. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0734189X85900167

[2] E. Rublee, V. Rabaud, K. Konolige, and G. Bradski, "Orb: An efficient alternative to sift or surf," in *2011 International Conference on Computer Vision*, Nov 2011, pp. 2564–2571.