# Segmentation and Classification of Fine Art Paintings

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## Introduction

In the area of image processing the semantic gap means that it is still not possible to create a system which can correctly identify any object in the image. This paper proposes a solution for classifying one sort of object- fine art painting. This approach includes segmentation of the painting from the image (3 methods), creation of the descriptor from the segmented painting (2 methods), and classification of the painting by matching its descriptor to the created database of original paintings. The solution proposed in this paper was tested on the database of the 15 original Rembrandt Harmenszoon van Rijn's paintings and the 100 photographs of the Rembrandt paintings photographed by tourists.

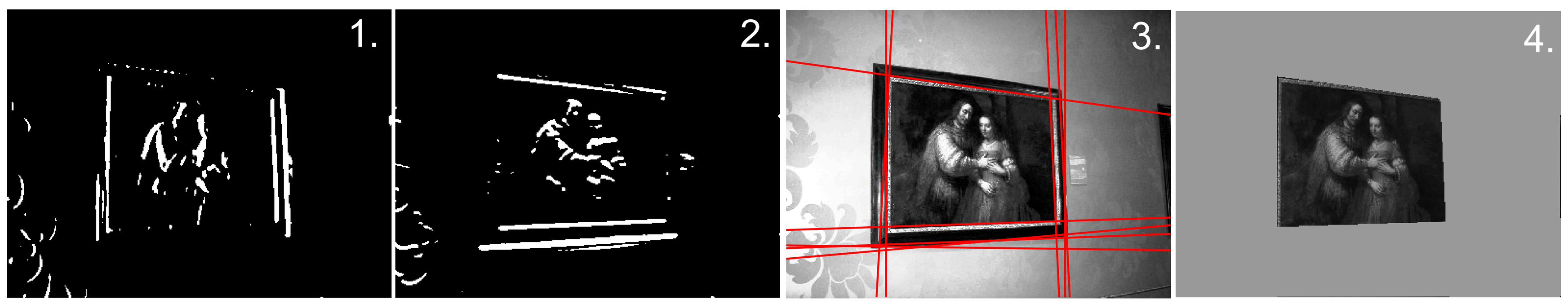
## A. Method

**1. Segmentation**
a. Gauss gradient
b. Anisotropic diffusion
c. Watershed

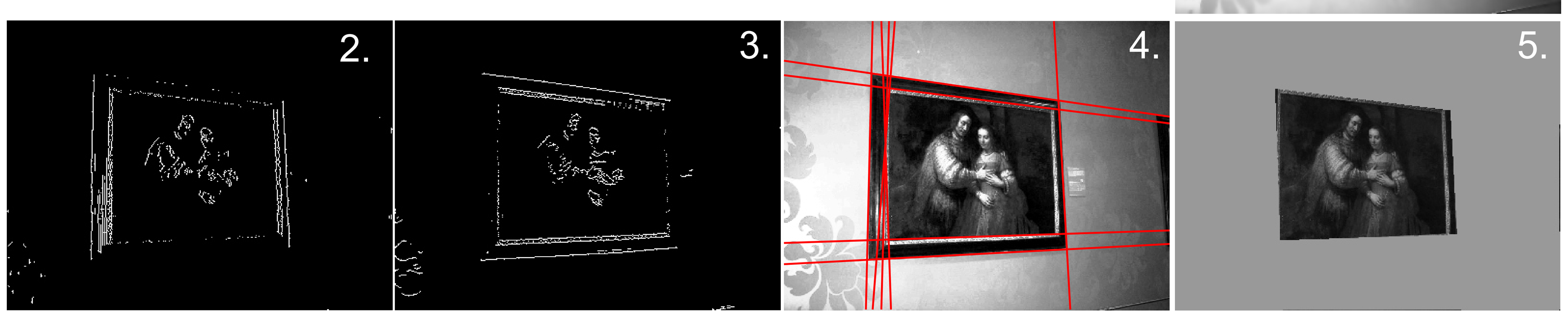
**2. Classification**
a. SIFT
b. SURF

### 1. Segmentation of the painting from the photograph

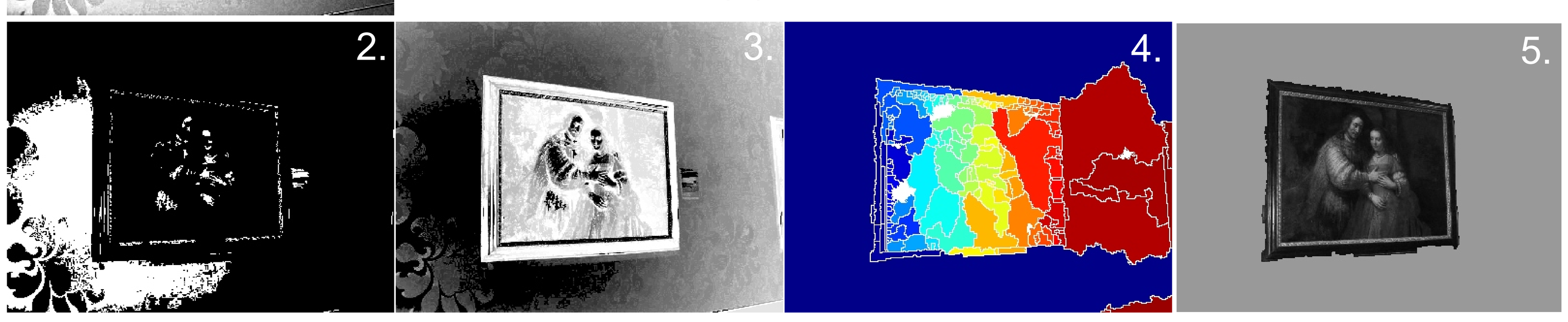
**a. Gauss gradient method**
1. Convert image to grayscale and equalize the histogram.
2. Use Gauss gradient (computes Gx (1), Gy (2) gradient images using 1st order derivative of the gaussian).
3. Find lines with Hough transform (3) in Gx,Gy images and connect or trim them based on their length.
4. Divide lines into upper, lower, left and right edges. Segment the painting as the smallest quadrilateral (4) created from these lines.




**b. Anisotropic diffusion method**
1, 4 similar to the a. method (5).
2. Filter image with Anisotropic diffusion (1) and convolve with Sobel filter (2,3) to find edges.
3. Find lines with Hough transform (4) in Sx, Sy Sobel images.


**c. Watershed method**
1. Create top and bottom hat of the image.
2. Create image I2= (I+ tophat) -bottomhat (1).
3. Create Im3 as extended minima(2). (regional minima of the H-minima transform) of Im2.
4. Make minima imposition(3) from the complement of Im2 with the marker Im3.
5. Create clusters with watershed(4).
6. Final segmentation: grow the background from the corners(5).


### 2. Classification of the segmented painting

+Create a descriptor for:
- all paintings from the database of originals (D1s)
- the painting segmented from the photograph (D2)

+Find the D1 best matching to the D2 with nearest neighbor method

Two different approaches to creation of the descriptor:

**a. SIFT**

Descriptor: - created form the interest points (IPs - local extremes in DoG)
size: - number of IPs x 128 values summarized from orientation histogram computed on sample points around each IP.

**b.SURF**

Descriptor: - detection of IPs is based of the Hessian matrix
size: - number of IPs x 64 values: 4 values (sum of Haar-wavelet responses and of their absolute values in the horizontal and vertical direction) for all of 16 subregions around IP.

### 3. Matching of the descriptors

**In both SIFT and SURF:** the best matching value between D1s and D2.
**Nearest neighbor**: the row with the smallest Euclidean distance.
**The matching value:** sum of D1 rows for which the nearest neighbor has value smaller than Distance ratio times the second nearest neighbor.
**Distance ratio:** SIFT = 0.6, SURF = 0.7.
**Problem:** SIFT and SURF are not 100% distinctive ==> wrong classification of paintings not present in the database.
**Solution:** treshold for the minimal matching value.

## B. Performance Evaluation

| Method | Gaussgradient | Anisotr. diffusion | Watershed |
|---|---|---|---|
| Correct segmentation | 73% | 89% | 49% |
| Under segmentation | 21% | 8% | 50% |
| Over segmentation | 6% | 3% | 1% |

Anisotropic diffusion -- smoothes color edges in the painting and edges in the background. Preserves edges of the frame.
Gauss gradient -- smoothes all edges uniformly.
Watershed -- not efficient for this purpose.

| Method | SIFT | SURF |
|---|---|---|
| Threshold=0 | 74% | 74% |
| Threshold=8 | 89% | 89% |
| Threshold=10 | 89% | 84% |

| Method | SIFT | SURF |
|---|---|---|
| time of the computation of the descriptor | 0,8125 s | 0,32025 s |

Percentage of properly classified paintings by SIFT and SURF with different **thresholds** for minimal matching value.
SIFT and SURF with threshold value 8 both achieved 89 % percent of succesfully classified paintings, but the SURF method is more than 2 times faster.

## C. Conclusion and Future work

Best results: **Anisotropic diffusion**+ **SURF** method

Future improvement: + integration of the probabilistic classification methods
+ extension of the database of the originals
+ implementation in Open CV

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**Bibliography**
Herbert Bay, Tinne Tuytelaars, and Luc Van Gool., “Surf: Speeded up robust features", in: Proceeding of the ECCV, pages 404--417, 2006.
David G. Lowe., “Distinctive image features from scale-invariant keypoints", in: International Journal of Computer Vision, 60, 2, pages 91--110, 2004.