Identifying centres of interest in paintings using alignment and edge detection. Case studies on works by Luc Tuymans *

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Abstract. What is the creative process through which an artist goes from an original image to a painting? Can we examine this process using techniques from computer vision and pattern recognition? Here we set the first preliminary steps to algorithmically deconstruct some of the transformations that an artist applies to an original image in order to establish centres of interest, which are focal areas of a painting that carry meaning. We introduce a comparative methodology that first cuts out the minimal segment from the original image on which the painting is based, then aligns the painting with this source, investigates micro-differences to identify centres of interest and attempts to understand their role. In this paper we focus exclusively on micro-differences with respect to edges. We believe that research into where and how artists create centres of interest in paintings is valuable for curators, art historians, viewers, and art educators, and might even help artists to understand and refine their own artistic method.

1 Introduction

There is already a significant body of research investigating artistic paintings using techniques from pattern recognition, computer vision and AI. For example, some researchers have used deep learning to extract patterns from a series of paintings in order to obtain a statistical model of the painter’s style and then

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create new images in the same style [14]. Others use neural networks for clas-
sifying paintings [3] or semantic web technology for organizing large collections
based on rich ontologies so that these collections can be searched in more pow-
nerful ways [2]. In addition, many projects have been using image processing to
assist in conservation work, artist identification, detection of forgery, and many
other applications [4]. This paper focuses on a new, complementary aspect of art
investigation, which attempts to understand the artistic creation process through
AI modeling.

We start from the hypothesis that an artist tries to stimulate a process of
narrative creation in the viewer and uses the expressive means available in the
chosen medium. In the case of painting, this includes objects and figures being
depicted, lines, colors, contrast, composition, blurring of background, etc. The
artist is in a sense engaged in a form of cognitive engineering [5], manipulating
the mental processes of viewers by shaping their sensory experiences and memory
recalls. The creation of an artistic painting is therefore more than the application
of a particular style to an existing image, as done in deep generative adversarial
neural network experiments [14]. A style can certainly be recognized by current
AI technology and even replicated, but the creation of an artwork is more than
achieving formal appearances in a particular style. It is about choosing a perti-
nent subject, transforming images into more powerful ones, and evoking a web
of meanings in the viewer.

Consequently, the interpretation of an artwork has a strong similarity with
the understanding of a text and the creation of an artwork is similar to the
production of a text, with the important difference that many of the meanings
expressed or invoked by paintings or works in other media, like music or dance,
are pre-verbal. They concern conceptualizations, emotions, moral values and
perspectives that are not so easy to put into words. These meanings resonate
with viewers at a subconscious level and, partly for this reason, they may evoke
a stronger reaction from the viewer than obtainable from a purely rational text.
Art works activate the non-rational, non-cognitive areas of the brain, such as
the emotion system [10] or the social brain [20].

A work of art is complex and rich because it evokes the different levels of
meaning (formal, factual, expressional, cultural, intrinsic) at the same time and
the meanings at each level intimately interact with others [12]. Moreover which
set of meanings resonates with one viewer is usually not the same as those res-
onating with another viewer or with those originally felt or intended by the artist,
simply because everybody has their own episodic and semantic memory, their
own prior experiences of artworks, their own social context and psychological
state when viewing, experiencing and interpreting an artwork. There is there-
fore no objectively ‘correct’ set of meanings and it would be futile to develop an
AI system that would extract such a set. However, this paper will try to show
that we can nevertheless study artistic methods, i.e. the kind of transformations
an artist performs on a real scene or a found image in order to induce meanings
in the viewer.

An important part of the artistic painting method consists in the introduction
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of visual centres of interest, attention getters which guide meaning invocation. They are instantiated partly by what is being represented, for example, an iconic image of a well known person which is appropriated by the artist, such as the well-known image of Marilyn Monroe used by Andy Warhol. Partly there are objects or parts of objects where the human vision system naturally pays attention to, for example the eyes of a face. And in addition, artists often introduce deviations from what is expected, for example they deform the nose on a face, or they use devices such as contrast, bright colors, sharp edges, blurring of background, flattening out of 3d effect, etc.

There is often a first most salient centre of attention, called the primary focal point, which pulls the viewer into the painting. For example, in the case of Figure 1 (left), the focal point is clearly the left eye and to a second degree the lips. The primary focal point introduces an organizing perspective from which the gaze of the viewer starts its exploration. Then there are additional focal points, as the viewers’ eye gaze glances over the different parts of the painting.

In earlier work in collaboration with Björn Wahle [16], we already used various computer vision methods to investigate how saliency identifies the primary focal point. The first set of saliency detection methods we tried on the Tuymans paintings were low-level, in the sense that they estimate saliency based on general statistitical properties of the visual image [16]. In this paper we introduce a complementary new and quite different methodology to study which areas in a painting are interest centres. The methodology is based on comparing an original source image (for example a photograph) with the painting based on it and deconstructing the interventions the painter undertook to transform one into the other. Many contemporary painters expressly use existing images from popular culture to make contact with their audience and thus comment on contemporary media culture. Our comparative methodology contains four steps:

(i) Locate the original image, either directly from the painter or searching information resources like images available on the world wide web or in image repositories using reverse image search.

(ii) Align the painting with the original image. This involves finding the minimal set of macro-operations performed by the artist, such as cutting, rotating, or scaling so that the contents of the painting are optimally aligned with the corresponding segment in the original image.

(iii) Zoom in on regions where there have been micro-transformations focusing on specific aspects of the painting, for example changes in shape, blurring, changes in illumination, edges differences, color changes, etc. The difference map between original image and painting for each of these aspects provides us with hypotheses what areas may be centres of interest and triggers inquiries in their possible meaning.

(iv) Importantly we then want to understand the meanings of these macro- and micro-transformations. This cannot be done at the moment with AI but introspection and conversations with the artist will help us to move in this direction in the future. In any case we have found that the suggestions coming out
of the previous steps are very illuminating because they tell us where to look. In any case, they have enriched the experience of paintings by the present authors.

2 Case studies

The present paper reports the first results from applying our comparative methodology using paintings by the contemporary Flemish painter Luc Tuymans. Working with a living artist makes it possible to validate our hypotheses about what the centres of interest are in a particular painting and they can tell us whether AI techniques have yielded anything worthwhile, not only for viewers, curators or art historians but also for those creating artworks themselves.

Luc Tuymans is considered to be one of the most important contemporary painters at the moment [19]. He has done solo exhibitions at some of the most prestigious and influential art centres in the world such as the MOMA in New York, the Palazzo Grassi in Venice, the MCA Museum of Contemporary Art in Chicago, BOZAR in Brussels, the Städel Museum in Frankfurt, the National Art Museum of Beijing, etc. We have been fortunate because we have a direct and recurrent contact with this painter and have access to the relevant parts of his digital archives. Moreover Luc Tuymans is very articulate in describing his own artistic method as well as the methods used by other painters [18].

We have constructed a general interactive pipeline of pattern recognition, computer vision and AI algorithms to apply our methodology and processed several paintings by Luc Tuymans. Here we only focus on those parts of the pipeline that involve alignment and edge detection. The paintings we have studied in detail so far have come from the solo exhibition of Luc Tuymans at the Palazzo Grassi in Venice (2019-2020) but we have also done experiments on all the paintings Luc Tuymans documented in his Catalogue Raisonné[11]. Given space limitations, we focus in this paper mainly on one specific painting, entitled K., shown in Figure 1 (left) where the focus on edge difference maps has been fruitful. But we also show a second example, entitled Secrets, shown in Figure 8, where a focus on edge differences has yielded less results, mainly because the changes at the edge level are too numerous - hence we get too many possible centres of interest.

3 STEP I. Finding the original image

Due to direct contacts with the artist, we have had access to several original sources for the Palazzo Grassi paintings, including the one for K. (see Figure 1 right). But we also wondered whether, with the massive availability of images on the web and the sophistication of current image recognition technology, it was possible to find the original source image using reverse image search with the painting as a key.

Interestingly, a reverse image web search with the painting K. did not deliver anything close to a possible source image for K., even though the source was also available on the web (see below). It appears that there are properties of
artistic paintings which make the use of reverse image search algorithms difficult, whereas a human observer immediately recognizes that the painting on the left of Figure 1 depicts the woman shown on the right. The issue of domain adaptation has become a recent hot topic in computer vision research but we have not applied these new methods yet [22].

On the other hand, once an original source image is available, reverse image search systems, like the one provided by Google or Bing, are able to locate this original and its variants, even if the provided original image is only a segment within a larger image or parts of the original image are not included. Thus using the original image in Figure 1 (right), we found the actual context of the original image. It turned out to come from an advertising campaign by Dior (see Figure 2), showing a clothing line designed by fashion designer Raf Simons and photographed by Willy Vanderperre, both alumni of the Antwerp art academy where Tuymans studied as well. The scene has been set up on the Normandy coast in France. Notice that in the advertisement, the top hair of K. is cut out which is not the case in the original image for K. provided by the painter.

Fig. 1. Left: ‘K.’ by Luc Tuymans, 2017, oil on canvas, 135 × 80.2 cm. Andrew Xue Collection, Singapore. Right: Source image as provided by the artist.

Fig. 2. Image from the Dior Autumn-Winter 2015 campaign with clothes designed by Raf Simons and photography by Willy Vanderperre. The fashion model to the left, the basis of K., is Julia Nobis.
Finding the original image of a painting is of interest from an art-history point of view and it provides important cues as to the factual and cultural meaning of the painting. This kind of fashion advertisement imagery - not necessarily this particular image - is familiar to everybody through magazines and posters and it reflects contemporary culture. Luc Tuymans expropriates the esthetic elements and the staging of the fashion models but at the same time removes completely the original context in order to create a timeless image.

4 STEP II. Aligning the painting and the original

The next step in our methodology is to align the original image with the painting. This is a very non-trivial image processing problem. For this paper, we did a manual selection of a possible candidate image, cutting out a segment that left out as much as possible of the material that was not in the painting, because we found that the vision algorithms we tried do not work well when there was too much additional extra material in the source image.

Given a good candidate, the alignment problem becomes similar to the so called image registration task \[9\] which is widely used in medical imaging, automated manufacturing, satellite navigation, and many other application fields for comparing or integrating data acquired from different sensors, at different times, or with different depth or viewpoints. Image registration algorithms fuse multimodal information or detect changes on such images. Given a set of two images, the one that will be transformed is called the moving image, and the one that is left unchanged, is called the reference image.

In the present investigation, we view the original image (the photograph) as the moving image and try to align it to the painting by progressively transforming the original image. The painting is therefore the reference image in image registration terminology. This is the perspective of the painter because the painter transforms the original image into a painting. Conversely, we can start from the painting, which now becomes the moving image, and try to align it to the original image, which now becomes the reference image, by transforming the painting to look similar to the photograph. This is in a sense the perspective from the viewer who sees the painting and then tries to align it with an image stored in his or her episodic memory. Both approaches yield interesting results, but in this paper we focus mainly on the painter’s perspective only.

Image registration has been discussed intensely in the computer vision literature and many algorithms exist, primarily feature-based or intensity-based methods \[9\]. Feature-based methods aim to find a correspondence between image features such as interest points, lines, and contours, while intensity-based methods aim to align pixel patterns via correlation or similarity metrics. In this paper, we will rely only on the multi-modal intensity-based registration method, implemented using the Matlab Registration Estimator App with its default parameters

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1 https://www.mathworks.com/help/images/register-images-using-the-registration-estimator-app.html
We also experimented with the feature-based approach trying to detect the candidate features on source and target images by various well-known algorithms, in particular, the Maximally stable extremal region method (MSER) [4] and the Speeded up Robust Features Method (SURF) [1]. However, we found that the output of the feature-based approaches performed poorly for the alignment task, possibly due to the significant gap between source and target images, as one is a photograph and the other a painting. Using features from these classical methods leads to the detection of too many low quality interest points to yield effective alignment.

![Flow diagram for image alignment of K](image)

**Fig. 3.** Flow diagram for image alignment of K. The top show the ‘viewer’s perspective’, using the painting as moving image and the photograph as reference image, and at the bottom, we show the ‘painter’s perspective’ with the photography as moving image and the painting as reference image. To show the overlay, the painting is rendered using a purple color and the original photograph using green.

We operationalized alignment using a best-first search algorithm, as used for example in [17]. The Mattes mutual information metric [13] is used to compute the similarity between source and target. It is shown in [13] that this metric leads to better alignment than the Mean Squares metric when the goal is to align images from different modalities using rigid transformations, which is the case here. The algorithm searches for a set of transformation parameters that produce the best possible alignment result. Given a matrix of transformation parameters \( M \), called the parent, a number of variations \( M_1, \ldots, M_n \), called the children, are generated, at first using aggressive perturbations. The perturbations include shape-preserving transformations like rotation, translation, isotropic scaling, and reflection. If a child \( M_i \)'s parameters yield a better alignment, then it becomes the new parent on the next iteration. But if a parent still yields a better result, it remains as a parent and new children are computed with less aggressive changes to the parent’s matrix.
5  STEP III. Micro-transformations

Once we have adequately aligned the original image with the painting, it becomes possible to inquire about the micro-transformations that the painter has introduced and their function. These variations have happened for different visual aspects, e.g. color, contrast, figure orientation, contours, etc. and so we need to first isolate these aspects from the image. In the rest of this paper we only look at edges, which means that we investigate which additional edges or edge variations the painter has introduced. The flow diagram of this pipeline is illustrated in Fig. [4] We have experimented with two algorithms, a traditional edge detection method, namely the Sobel Isotropic $3 \times 3$ gradient operator (SOBEL), and a deep neural network known as the Traditional Inspired Network (TIN) recently introduced by Wibisono and Hang [21].

The SOBEL edge detection method has been a very popular and widely used algorithm in image processing since 1968 [15]. It is based on derivation of a simple and computationally efficient gradient operator. In order to calculate the approximations of derivatives for horizontal and vertical intensity changes, the gray-scaled input image is convolved with two $3 \times 3$ kernels as follows:

$$G_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \ast I \quad G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \ast I$$

where $I$ denotes the input image in grayscale, $G_x$ and $G_y$ are two images which at each point contain the vertical and horizontal derivative approximations. Then,

![Flow diagram for edge detection. It shows the edge maps for K. on top for the painting and below for the original image at different scales based on the TIN method. The difference map is shown with purple for the photograph, green for the painting and black when edges overlap.](image-url)
the resulting gradient approximations are combined to have the gradient magnitude at each point in the image, using \( G = \sqrt{G_x^2 + G_y^2} \). Subsequent images showing the results of the Sobel Method, display this gradient magnitude \( G \).

Deep neural network frameworks have originally been designed for high-level computer vision tasks such as object recognition or scene understanding through semantic segmentation. Edge detection is a more local and simpler task so that a lightweight deep learning network can provide high quality edges with reduced computational complexity. This approach has been adopted by the Traditional Method Inspired Network (TIN) proposed very recently by Wibisono and Hang [21] with reported state of the art accuracy performances on the BSDS500 test set. The framework is composed of three modules, i.e., Feature Extractor, Enrichment, and Summarizer, which roughly correspond to gradient, low pass filter, and pixel connection in the traditional edge detection schemes. The pre-training of the TIN method was performed on three datasets of natural images BSDS500.

In our experiment, we used the published code² by the authors and we used their pretrained model on the aforementioned datasets for the proposed architecture TIN2, since higher performances were reported by TIN2 compared to TIN1 in [21]. To make a fair comparative analysis between the SOBEL and TIN methods, we applied the same post-processing operation, namely Non-Maximum Suppression (NMS), to both edge-detection methods, i.e. we computed edge maps at different scales, 1.5x, 1x, 0.5x, for both the origin and target, took the average of these maps, and resized the edge maps to the original image size, i.e., \( x = 1000 \). As mentioned in [21], this procedure provides better-located edges.

![Fig. 5. Comparison of two edge detection methods, taking the painter’s perspective (going from photograph to painting). The painting edges are in green and the photograph edges in purple. Left: the difference map for the SOBEL method. Middle: the difference map for the TIN method. We see that the TIN method provides clearer edges showing the variations introduced by the painter in a clearer way.](image)

² [https://github.com/jannctu/TIN](https://github.com/jannctu/TIN)
Finally, we compute the edge difference maps for further analysis. Figure 5 shows the outcome after thresholding in order to binarize the edge map so that the significant edges stand out more. Before such a thresholding operation, SOBEL had provided a more noisy edge detection map than TIN. However, after thresholding we observe that while some edges detected by TIN were preserved, some edges detected by the SOBEL method were removed. As TIN preserved better significant edges, we proceed for further analysis with the edges detected by the TIN method.

We now can compute centres of interest, being those areas on the painting for which there are significant differences between the two edge maps. The algorithm proceeds in three steps: [i] Compute first the bounding boxes around the thresholded edges only contained in the painting, so neither in the picture only nor in both. Only those edges are retained which form an area containing more than \( a \) points (pixels) with a perimeter containing more than \( p \) points. The bounding box is extended slightly (with an addition of \( c \)). [ii] Concatenate neighbors of bounding boxes by merging overlapping boxes from step [i] into larger boxes. [iii] Step [ii] is iterated until there are no overlapping bounding boxes. The different parameters \( a, p, \) and \( c \) allow us to tune these steps to get more or fewer centres of interest. Results are shown in Figure 6. (i) shows the result of step [i] with \( a = 100, p = 70, \) and \( c = 0.0023 \). (ii) shows the result of step [i] projected on the painting. (iii) shows the result of applying step [ii] for two iterations at which point there are no more overlapping bounding boxes.

![Fig. 6. Computing the centres of interest based on edge difference maps. (i) Aggregation of edge differences. (ii) Projection of aggregation on painting. (iii) Expansion of bounding boxes.](image)

We see in Figure 6(iii) that the following centres are proposed: (a) the lips area at the bottom, specifically the right side of the lips ('right' from the perspective of the person being depicted), (b) the right eye and the area around it, specifically the region where the eyebrow reaches the top of the nose, the pupil and the line under the right eye, (c) the nose area with the nostril and the curve at the right wing of the nose, (d) the left eye, particularly the corner with the nose, and (e) the region above the left eye.
6 STEP IV. Deconstructing possible meanings

Do these newly discovered centres of interest make any sense? A closer look at the original photograph and the painting shows that there is actually a subtle difference in facial expression between the photograph and the painting. This becomes clearer if we compare the centres of interest projected on the edge map of the painting (ii) and the photograph (iii) (see Figure 7).

![Fig. 7. Edge maps with centres of interest (TIN method). (i) Projection on edge map of painting, (ii) Projection on edge map of original photograph.](image)

We see that on the painting, the facial expression of K. is more open and presents a weak smile, whereas on the photograph, the expression is more sturdy and closed. The more open facial expression is achieved by very subtle changes. The left corner of the lips in the painting is curled upward, the nostril more pronounced, the eye pupil bigger, the eyebrows showing a clearer V-shape, and the line under the left eye being more visible. These changes are subtle and unconscious to the viewer but they have an impact on the interpretation process, as they all point to a more open weakly smiling facial expression.

To see whether this interpretation has any validity. It is instructive to consider a ‘gold standard’ narrative about painting K. offered by Marc Donnadieu, chief curator of the Musée de l’Elysée in Lausanne and published in the guidebook of the La Pelle exhibition at the Palazzo Grassi in Venice:[6]

"The artist was inspired by advertising billboards he saw in Panama, which feature women’s faces that have been smoothed out to the point of erasing their personality. As a filmmaker would do, he zoomed on this face so close that it is partially cut out and incomplete. By moving his ‘paintbrush camera’ so close he treats this female face as if it was an object, which is precisely the purpose of advertising, in particular when selling beauty products. This approach renders the face empty, almost dead, especially because it is not contextualized. But by zooming this way, the artist also highlights the gaze of this woman who has been so
objectified that she doesn’t even have a name, just a letter, K. And her gaze is very expressive, as if she tried to exist beyond the image and the commercial profit that is sought through her. She seems defiant, aware that she is exploited and ready to stand up as she looks far ahead, maybe towards a future where women will not be treated as objects. The treatment is smooth, flat, and the pastel colors highlight the contrast between the artificial aspect of advertising imagery and the humanity of all women. K’s mouth is shut, but she smiles discreetly and her silence speaks volumes.

The painting may be inspired by billboards in Panama on beauty products, although we have seen that the direct inspiration are fashion models from an advertising campaign of Dior. Nevertheless the way women are represented is undoubtedly similar. There is an objectification \[8\] of the human body, more concretely in this case of the human face. This objectification is present in the photography but even more so in the painting: The extreme focus on the face so that there is an almost complete elimination of the context, the use of pastel color, the flat treatment of the skin to smoothen out details that make natural faces alive, the choice of a letter K. for the title of the painting, instead of a real name. Marc Donnadieu mentions expressional meanings like: ‘smile discreetly’, ‘defiant’, ‘expressive gaze’ which confirm the subtle changes in lips, eyes, eyebrows and nose that the edge-based comparative methodology detected. This example therefore illustrates the idea that AI methods can act like a microscope that draws attention to interest regions and helps us see details that would otherwise remain unconscious.

7 A second case study

We now show very briefly a second example from the 2019-2020 Palazzo Grassi solo exhibition by Luc Tuymans, a painting entitle Secrets. It depicts one of the main figures of the Nazi regime, Albert Speer, who has always denied any knowledge of the Holocaust atrocities. Figure 8 shows first the painting as well as the source image, which has been cropped from a larger image that shows Speer in full Nazi regalia. Figure 8 shows next the results of using the same alignment process as used for K., both for aligning the picture on the painting and the painting on the picture.

We see that the alignment algorithm works very well, even though this case is much more challenging as the face is slightly rotated, stretched along the y-axis and squeezed along the x-axis. Figure 9 shows the results of edge detection using the TIN method with the difference map projected on the photograph. Again the results are very satisfactory. Finally, Figure 10 shows the same operations as in Figure 9 now on the edge difference map of ‘Secrets’. Again we have to ask whether the regions identified through this process function as meaningful centres of interest. Unfortunately there are clearly too many regions to allow a meaningful analysis, mainly because there are a lot of changes that the artist has made to the original source image. These changes are all purposeful. They
Fig. 8. From left to right: (i) painting, (ii) original photograph, (iii) alignment picture on painting (iv) aligning of painting on picture.

have to do with making the face more geometric, closed-off, inward-looking and in denial. Most probably using other aggregation algorithms could lead to more useful results.

Fig. 9. From left to right: (i) edges from painting, (ii) edges from aligned photograph, (iii) edge difference map painter’s perspective.

Fig. 10. Computing the centres of interest based on edge difference maps. (i) Aggregation of edge differences. (ii) Projection of aggregation on painting. (iii) Expansion of bounding boxes.
8 Conclusions

It is well known that painters never attempt to paint exactly a chosen image (or a real world scene) but transform it to achieve an artistic purpose - except in artistic movements where realism is in itself an artistic statement, like in hyper-realistic art. This paper reported on attempts to deconstruct algorithmically what transformations a contemporary painter carried out and discussed in how far paying attention to the regions identified by this process helps us in the construction of a narrative capturing the meanings invoked by a painting. AI algorithms are used here as microscopes that allow us to look in detail at transformations which are normally only experienced at a subconscious level.

This paper focused on edge differences only. In one case study (the painting entitled K.), the regions found through comparing edge differences indeed point to centres of interest that can be interpreted. In the second case study (‘Secrets’) alignment and edge detection worked well but useful conclusions in terms of centres of interest could not be reached. These examples show that the comparative method is only at its first beginning. There are other dimensions of transformation that must be studied in equal detail and color is the most likely candidate. More generally, the hard but certainly fascinating, work remains to see how far the type of analysis proposed here can help to recognize and label the objects in a painting, detect the general mood, the emotions being expressed by the depicted figures, and much more, all in the service of supporting narrative construction in viewers.

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