The role of motion dynamics in abstract painting

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Abstract

We investigate the role of dynamic motions performed by artists during the creative process of art generation. We are especially interested modern artworks inspired by the Action Painting style of Jackson Pollock.
Our aim is to evaluate and model the role of these motions in the process of art creation. We are using mathematical approaches from optimization and optimal control to capture the essence (cost functions of an optimal control problem) of these movements, study it and transfer it to feasible motions for a robot arm. Additionally, we performed studies of human responses to paintings assisted by an image analysis framework, which computes several image characteristics. We asked people to sort and cluster different action-painting images and performed PCA and Cluster Analysis in order to determine image traits that cause certain aesthetic experiences in contemplators.
By combining these approaches, we can develop a model that allows our robotic platform to monitor its painting process using a camera system and – based on an evaluation of its current status – to change its movement to create human-like paintings. This way, we enable the robot to paint in a human-like way without any further control from an operator.

Introduction

The cognitive processes of generating and perceiving abstract art are – in contrast to figurative art – widely unknown. When processing representational art works, the effect of meaning is highly dominant. In abstract art, with the lack of this factor, the processes of perception are much more ambiguous, relying on a variety of more subtle qualities. In this work, we focus on the role of dynamic motions performed during the creation of an art work as one specific trait that influences our perception and aesthetic experience.

Action Paintings - Modern art works created by dynamic motions

The term "action painting" was first used in the essay "The American Action Painters" (Rosenberg 1952). While the term "action painting" is commonly used in public, art historians sometimes also use the term "Gestural Abstraction". Both terms emphasize the process of creating art, rather than the resulting art work, which reflects the key innovation that

Figure 1: An action painting in the style of Jackson Pollock, painted by "JacksonBot"

arose with this new form of painting in the 1940s to the 1960s. The style of painting includes dripping, dabbing and splashing paint on a canvas rather than being applied carefully and in a controlled way. Art encyclopedias describe these techniques as "depending on broad actions directed by the artist's sense of control interacting with chance or random occurrences." The artists often consider the physical act of painting itself as the essential aspect of the finished work. Regarding the contemplators, action paintings intend to connect to them on a subconscious level. In 1950, Pollock said "The unconscious is a very important side of modern art and I think the unconscious drives do mean a lot in looking at paintings"(Ross 1990) and later, he stated "We're all of us influenced by Freud, I guess I've been a Jungian for a long time"(Rodman 1961). Clearly, artists like Pollock do not think actively about dynamic motions performed by their bodies the way as mathematicians from the area of modeling and optimal control do. But for us, it is very exciting, that one of the main changes they applied to their painting style in order to achieve their aim of addressing the subconscious mind has been a shift in the manner they carry out their motions during the creational process.

Understanding the perception and generation of action paintings

Since a human possesses much more degrees of freedom than needed to move, human motions can often be seen as a superposition of goal directed motions and implicit, unconscious motions. The assumption, that elements of human motions can be described in this manner has been widely applied and verified, particularly in walking and running motions (Felis and Mombaur 2012),(Schultz and Mombaur 2010), but also (very recently) regarding emotional body language during human walking (Felis, Mombaur, and Berthoz 2012). If we transfer this approach to an artist, the goal-directed motions are those carried out to direct his hand (or rather a brush or tool) to the desired position, the implicit, unconscious motions are the result of an implicit solved optimal control problem with a certain cost function like maximizing stability or minimizing energy costs.

When looking at action paintings, we note, that this form of art generation is a very extreme form of this superposition model with a widely negligible goal-directed part. Therefore, it is a perfect basis to study the role of (unconscious) motion dynamics on a resulting art work. Jackson Pollock himself expressed similar thoughts when he said "The modern artist... is working and expressing an inner world – in other words – expressing the energy, the motion, and other inner forces" or "When you're working out of your unconscious, figures are bound to emerge... Painting is a state of being" (Rodman 1961).

However, the role of motion dynamics in the embodied expression of artists has been poorly described so far, supposedly due to the lack of an adequate method for the acquisition of quantitative data. The goal of our project is to use state-of-the-art tools from scientific computing to analyze the impact of motion dynamics both on the creational and perceptual side of action-painting art works. Therefore, we perform perception studies with contemplators and experimental studies concerning motion generation, which are linked by a robotic platform as a tool that can precisely reproduce different motion dynamics. Using this approach, we want to determine key motion types influencing a painting's perception.

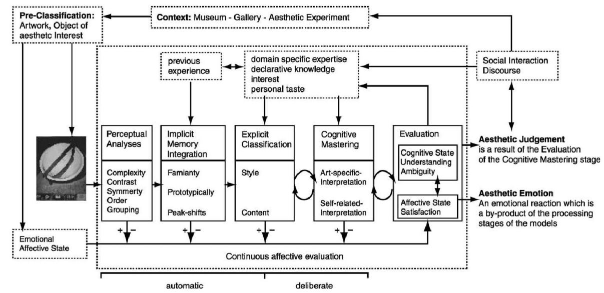

Figure 2: Overview of the aesthetic judgment model by (Leder et al. 2004)

Models of art perception

The perception of art, especially abstract art, is still an area of ongoing investigations. Therefore, no generally accepted theory including all facets of art perception exists. There are, however, different theories that can explain different aspects of art perception. One example of a theory of art perception is the one presented in (Leder et al. 2004) (see figure 2). In the past, resulting from an increasing interest in embodied cognition and embodied perception, there has been a stronger focus on the nature of human motion and its dynamics regarding neuroscience or rather neuroaesthetics as well as psychology and history of art. There are several results, showing that we perceive motion and actions with a strong involvement of those brain regions that are responsible for motion and action generation (Buccino et al. 2001). The mirror neurons located in these brain regions fire both, when an action is actively performed and when the same action is being observed. These findings support the theory, that the neural representations for action perception and action production are identical (Buxbaum, Kyle, and Menon 2005). The relation between perception and embodied action simulation also exists for static scenes (Urgesi et al. 2006) and ranges even to the degree, where the motion is implied only by a static result of this very motion. For example, (Knoblich et al. 2002) showed, that the observation of a static graph sign evokes in the brain a motor simulation of the gesture, which is required to produce this graph sign. Finally, in (Freedberg and Gallese 2007), it was proposed that this effect of reconstructing motions by embodied simulation mechanisms will also be found when looking at "art works that are characterized by the particular gestural traces of the artist, as in Fontana and Pollock".

Mathematical background

To perform mathematical computations on motion dynamics, we first need to create models of a human and the robot arm. Both can be considered as systems of rigid bodies, which are connected by different types of joints (prismatic or revolute). By "model", we mean a mathematical description in terms of differential equations of the physical characteristics of the human arm an the robot accordingly. Depending on the number of bodies and joints, we end up with an certain number of degrees of freedom. For each body, we get a set of generalized variables q (coordinates), $\dot{q}$ (velocities), $\ddot{q}$ (accelerations), and τ (joint torques). Given such a model, we can fully describe its dynamics by means of

$$M(q)\ddot{q} + N(q, \dot{q}) = \tau \qquad (1)$$

where $M(q)$ is the joint space inertia matrix and $N(q, \dot{q})$ contains the generalized non-linear effects. Once we have such a model, we can formulate our optimal control problem using $x = [q, \dot{q}]^T$ as states and $u = \tau$ as controls. The OCP

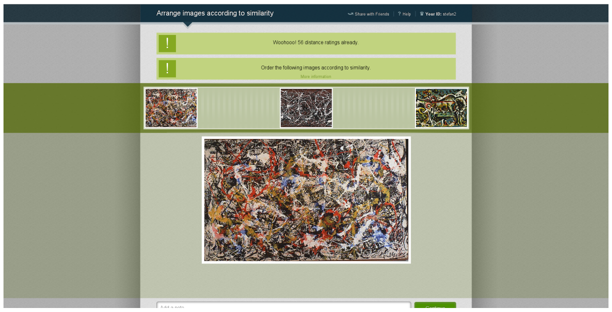

Figure 3: Interface for web-based similarity ratings

can be written in its general form as:

$$\min_{x,u,T} \int_0^T L(t, x(t), u(t), p)dt + \Phi_M(T, x(T)) \tag{2}$$

subject to:

$$\dot{x} = f(t, x(t), u(t), p)$$
$$g(x(t), p) = 0$$
$$h(t, x(t), u(t), p) \geq 0$$

Note, that all the dynamic computation from our model is included in the RHS of the differential equation $\dot{x} = f(t, x(t), u(t), p)$. The first part of our objective function, $\int_0^T L(t, x(t), u(t), p)dt$ is called the Lagrange term, $\Phi_M(T, x(T))$ is called the Mayer term. The former is used to address objectives that have to be evaluated over the whole time horizon (such as minimizing jerk), the latter is used to address objectives that only need to be evaluated at the end of the time horizon (such as overall time). In our case, we will often only use the Lagrange term. To solve such a problem numerically, we apply a direct multiple shooting method which is implemented in the software package MUSCOD-II. For a more detailed description of the algorithm, see (Bock and J. 1984; Leineweber et al. 2003).

Experimental Data

Perception experiments

We performed two pre-studies to find out, whether human contemplators can distinguish robot paintings from human-made paintings and how they evaluate robot paintings created by different mathematical objective functions.

In the first study, we showed nine paintings to 29 participants, most of whom were laymen in arts and only vaguely familiar with Jackson Pollock. Seven paintings were original art works by Jackson Pollock and two paintings were generated by the robot platform JacksonBot. We asked the participants to judge, which of the paintings were original paintings by Pollock and which were not, but we intentionally did not inform them about the robotic background of the "fake" paintings. As might be expected, the original works by Pollock had a higher acceptance rate, but,

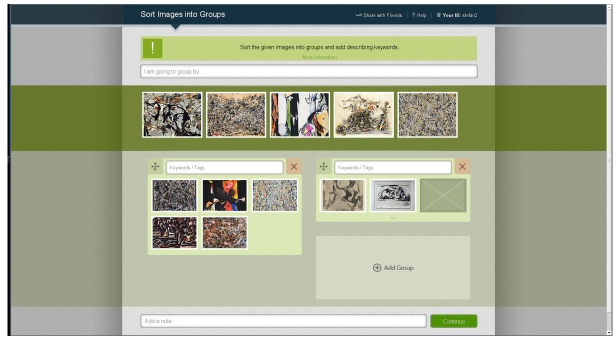

Figure 4: Interface for web-based sorting studies

very surprisingly, the difference between Pollock's and JacksonBot's paintings was not very high ($2.74 +/- 0.09$ vs. $2.85 +/- 0.76$, on a scale of 1 - 5).

In the second study, the participants were shown 10 paintings created solely by the robot platform, but with two opposite objective functions (maximum and minimum overall angular velocity in the robot arm) in the optimal control problem. The participants easily distinguished the two different painting styles.

Since the pre-studies were only conducted to get a rather rough idea on this aspect, we developed a more sophisticated web-based platform for further, more detailed investigations on this subject. The data obtained from this tool can be used to enhance the robot's ability to monitor its painting process.

The set of stimuli used for our studies consists of original action-art paintings by Pollock and other artists and images that were painted by our robot platform.

In the first task, contemplators are presented three randomly chosen paintings[1] and asked to arrange them on the screen according to their similarity (see figure 3). If they want, they are free to add a commentary to indicate their thoughts while arranging the paintings. As a result, we obtain for every set of two paintings a measure for their similarity in comparison with any other set of two paintings[2]. Using standard procedures from statistics like cluster analysis, we can determine which paintings are overall rated more "similar" than others.

In the second task, people are asked to perform a standard sorting study, i.e. they are asked to combine similar paintings in groups and to give some information on why they formed specific groups. The results of this task are used to validate the information obtained by the previous one and, additionally, they are used to gain more information about the attributes and traits, people seem to use while grouping. Therefore, the set of possible tags for the formed groups is limited and chosen by us. Is includes very basic image characteristics like colour as well as more interesting character-

[1]more precisely, the paintings are not chosen purely random but there is a slight correction to the probability of each painting to be presented in order to get many different correlations even when participants only complete few repetitions

[2]Note that we do not use the absolute values of "similarity" but quotients of these in order to avoid offset problems

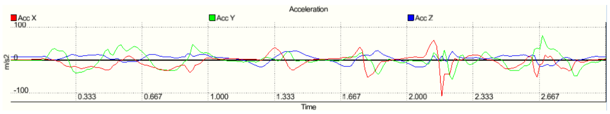

Figure 5: recorded acceleration data for a 3sec motion

istics like associated emotions.

Motion capture experiments

In order to study the way real human artists move during action-painting, we chose to do motion-capture studies with our collaborating artist. As a first approach, we used three inertia sensors to record dynamic data $D_{capture}$. For each of the three segments of the artist's arm (hand, lower arm, upper arm), we recorded accelerations, angular velocities and the rotation matrix[3] using three Xsens MTw inertial motion trackers. The sensors were placed directly above the calculated center of mass of each arm segment. Figure 5 shows an example of the raw data output obtained from the sensors.

We asked the artist to create different paintings and to describe her creative ideas as well as her thoughts and emotions during the process with her own words. That way, we can correlate identified objective functions with specific emotions or creative ideas.

Robot painting experiments

For first experiments, we created paintings with our robot platform. In order to compute the robot joint trajectories necessary to move along a desired end effector path, we use an optimal control based approach to solve the inverse kinematics problem. Using our first robotic platform, we created several paintings using different cost functions in the optimal control problem. Two of them – maximizing and minimizing the angular velocities in the robot joints – resulted in significantly different paintings. These paintings were used in the pre-study mentioned earlier.

Data Analysis

Motion reconstruction

To fit the record dynamic data $D_{capture}$ to our 9 DOF model of a human arm that is based on data from (De Leva 1996), we formulated an optimal control problem which generates the motion $x(t) = [q(t), \dot{q}(t)]^T$ and the controls $u(t) = \tau(t)$ that best fit the captured data with respect to the model dynamics f.

$$\min_{x,u} \frac{1}{2} ||D_{capture}(t) - D_{Simulated}(t)||_2^2 \qquad (3)$$

subject to:

$$\dot{x}(t) = f(t, x(t), u(t), p)$$
$$g(x, p) = 0$$
$$h(x, p) \geq 0$$

[3] recording the euler angles is not sufficient due to potential singularities in the reconstruction process

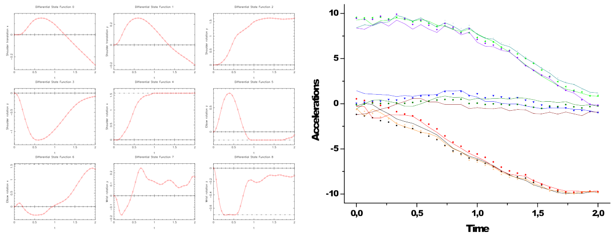

Figure 6: Computed trajectories for joint angles (left) and comparison of computed (lines) and measured (dots) accelerations (right).

The constraints in this case are given by the limited angles of the human arm joints and torque limitations of the arm muscles. The computed states and the fit quality of the acceleration data can bee seen in figure 6. Note that the angle approach to the joint limitations is plausible for this type of motion.

In the next step, we will use the motion capture data obtained from experiments with our collaborating artist not only reconstruct the motion, but use an inverse optimal control approach (like successfully used in a similar case in (Mombaur, Truong, and Laumond 2010)) to retrieve the underlying objective functions of these motions. To do so, we will use an approach developed by K.Hatz in (Hatz, Schlöder, and Bock 2012). This process is illustrated in figure 7.

Conclusion and Outlook

We introduced a new way to analyze the creative process of action painting by investigating the dynamic motions of artists. We developed a mathematical model, which we used to succesfully reconstructed an artists' action-painting-motions from inertia measurements. We used state-of-the-art optimal control techniques to create new action-painting-motions for a robotic platform and evaluated the resulting painting. Even with "artificial" objective functions, we were able to create action paintings that are indistinguishable from human-made action paintings for a human contemplator.

In the next step, we will use an inverse optimal control approach to go one step further from reconstructing an artist's motions to identifying the underlying objective functions of motion dynamics. That way, we will be able to generate specific painting motions corresponding to specific intentions as formulated by the artist.

Since several studies, e.g. (Haak et al. 2008), have shown that aesthetic experiences and judgments can – up to a certain degree – be explained by analyzing low-level image features, we chose to develop an image analysis software tool based on OpenCV that uses a variety of different filters and image processing tools that are related to aesthetic experience. Amongst other features, our tool analyzes the paintings considering its power spectrum, different symmetries, color and fractal analysis (Taylor, Micolich, and Jonas 1999). We will include the information obtained from our online perception studies in this tool and use it as feedback

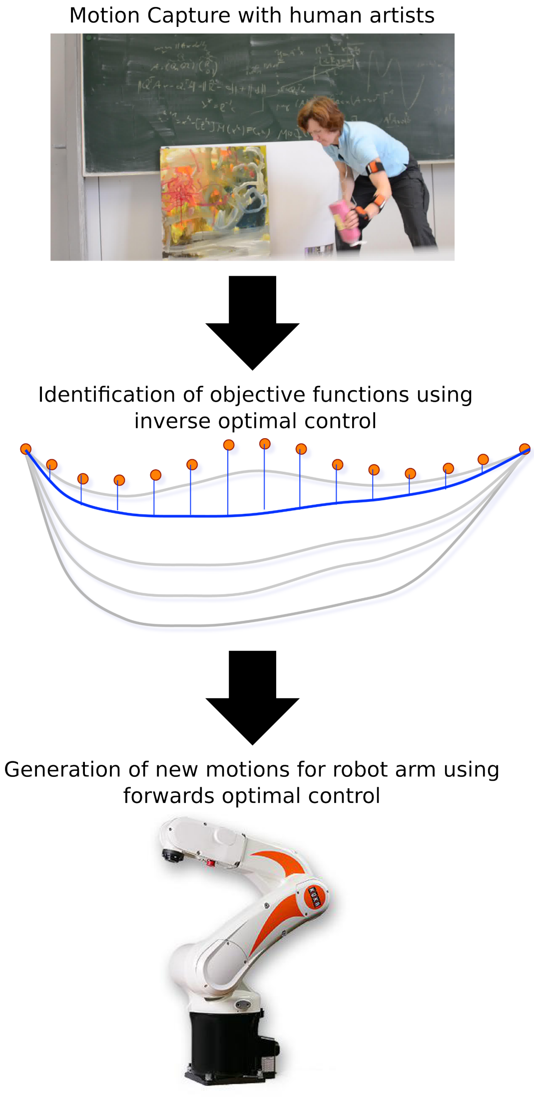

Figure 7: Transfer of human motion objectives to a robot platform (schematic overview)

for the robot platform. That way, we will enable it to paint autonomously with feedback only from an integrated camera monitoring the process.

The presented approach of capturing the essence of dynamic motions using inverse optimal control theory is not limited to the investigation of action paintings but can be used to analyze human motions in other art forms like dance or even in daily life by analyzing human gestures or full-body motions.

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