Interactive Machine Learning (IML) - Gesture Recognition in the Visual Arts

Abstract

The rapid development of machine learning technology has allowed artists to break through the limitations of the past and begin to use interactive systems created by machine learning algorithms such as supervised learning to explore their art intuitively in their own way. The use of gestural interfaces among others is the signature point that inspired the application of interactive machine learning for a wide range of art making applications (Christopher, He and Kapur, 2013)). The aim of this thesis is to explore the interactive representation of gesture recognition in machine learning for the visual arts, and this is achieved by exploring a range of topics including applications of machine learning in the arts, different studies and proposed approaches to building interactive machine learning systems, scalable interactions for gesture recognition, interactive machine learning tools and processes for use, and principles of practice in the visual arts.

The significance of this theme stems from the deep desire to understand how artists use machine learning to construct artworks, supported by the findings and experiences from the chapter studies, to enable the interaction of gesture recognition with visual graphic parameter spaces through technical practice. This paper therefore includes an analysis of a practical study of an individually created gesture recognition interaction interface that validates aspects of IML that can be contributed to artistic creation through changing visuals.

Introduction

The rapid development of machine learning has made it a new way to convey artistic creativity. For example, a simple recurrent neural network is trained to generate stunning visual images, and the style transfer algorithm transfers the style image to the content image, and predicts the next note or chord based on the LSTM neural network. These creative processes are completed by computer calculations and it is difficult to define whether it is art, and the way people see it determines what is art (Beedkar & Wadhekar, 2020). IML enables these typical machine learning tasks with the intervention of manual input, and the interaction process is more humane, diversified, and intelligent (Chen, Shidujaman, Jin & Ahmed, 2020). Among them, the gesture recognition algorithm has received extensive attention in the field of human-computer interaction and the field of visual art. Gesture recognition is a natural way of human-computer interaction. It can be an effective communication tool and enhance visual expression. A lot of current IML literature research is based on gesture recognition research. The interactive experience and content mapping of gesture changes are the goals pursued in many artistic creations, but most machine learning algorithms cannot guide non-professionals to construct artistic interactive works, because systems built by programmers often focus on technical iterative optimization and The data model of the work is evaluated, and the artist hopes to use the power of machine learning algorithms in an interactive way to let people participate in his art. Therefore, from the perspective of artistic creation, studying the needs of IML and the result feedback of IML in artistic applications can bring new research directions to the construction of interactive machine learning systems to a certain extent. The aim of this paper is to investigate the interaction capabilities of gesture recognition in interactive machine learning systems being applied to the visual arts domain, thereby supporting practical research in the creation and testing of gesture-recognised interactive interfaces.

1.2 Aims and Objectives

This article chooses to study the interactive mode of gesture recognition in the field of visual art, because there are many subjects engaged in visual research, such as photography, film, digital media, games, etc., which provide a basis for analysis and comparison. The user interface design of the IML system has been recognized as one of the tools for enhancing artistic practice in the art field. The goal is to achieve a changeable visual art effect, and to refer to and evaluate gesture interaction languages in different fields based on the selected technical process. Analyze the main points of gesture recognition in machine learning to construct visual art. The final analysis of creative opportunities will be presented in the gesture recognition system of visual image classification. Based on the application experience of gesture interaction in the field of art, the results of the research will analyze and evaluate which gesture interaction methods are the key to machine learning to enhance the practice of visual art.

1.3 Description of content

The second chapter of this article will introduce the relationship between ML and IML, the research field of gesture recognition, and the machine learning art works created in different fields. The third chapter will discuss in depth the design decision and construction methods for the project research, which will include the chosen visual art type (image vision) and visual design principles, gesture interaction language in gesture recognition, and the construction methods of interactive machine learning system. Chapter 4 will convey the design results and record the technical realization process of the project. Chapter 5 will critically discuss the research objects and research results. Chapter 6 contains a summary of the main points of the article and the final research conclusions.

Related work

2.1 Relationship between ML and IML

In recent years, the rapid development of algorithms such as deep learning and supervised learning has enabled machine learning to gradually penetrate and penetrate into all areas of life. Among them, the achievements of machine learning in the art world have changed people's traditional artistic concepts. Interactive systems make machine learning not only a tool to help humans create, but also creative entities (López de Mántaras, 2016). It can provide a way for people to participate in building machine learning models. The refinement of the model is driven by user input, and the user can input various forms of data using indicative samples as examples. However, standard machine learning is non-interactive. They only output the model through the input training data. Machine learning is a set of statistical analysis methods, all behaviors are controlled by parameters (Ware, Frank, Holmes, Hall & Witten, 2001). To complete tasks by learning from examples, there are many different learning strategies including supervised learning, semi-supervised learning, and so on. The input provided to the learning algorithm includes input in the form of tags, presentations, corrections, rankings, or evaluations. Machine learning heavily involves interaction with humans and therefore research related to interactive machine learning systems is gradually expanding. For art practitioners, it allows to find new artistic expression interfaces in an interactive way. Artists and other non-technical professionals can connect complex ML theories and algorithms with improved ML accessibility through an intuitive GUI when building IML, and can also choose specific ML models, such as classification, regression, or dynamic time warping models. (Plant, Zbyszynski, Gonzalez, Hilton, Fiebrink, Gibson & MartelliB, 2020). In general, IML is more dependent on the understanding of human-computer interaction than ML, and it makes machine learning techniques easier to use.

2.2 Research areas in gesture recognition

As the most important part of communication between people, gestures have different definitions in different fields. Therefore, gesture recognition algorithms in machine learning represent a broad field of research. In the field of human-computer interaction, gestures are body movements (Gillies, 2019) and the main goal of gesture recognition is to create a system that recognizes specific gestures and uses them to convey information or control devices. The technology used to input gestures is subdivided according to the gesture context. Different classification methods will affect the designed gesture recognition system, including environmental factors, gesture types, execution objects, devices used to capture gestures, and system applications (Mohammed, Waleed & Albawi, 2021). Various techniques for analyzing gesture systems have been established. One is sensor-based technoloques that primarily requires people to wear sensors as input devices, such as gloves and bracelets. The advantage of these technologies is that the recognition of gestures will not be distracted by diverse backgrounds, but it is accompanied by the trade-offs of lack of natural interaction, bulkiness, and high cost. The second is that vision-based technology uses capture devices such as cameras or motion sensors to input information based on how people perceive the surrounding environment. The effectiveness of these technologies depends on factors such as the number of cameras and their positioning, the visibility of the hands and how they are separated from the image, the efficiency of extracting features, and classification techniques (Mohammed, Waleed & Albawi, 2021). Examining the performance of machine learning technology in recognition programs based on vision and sensor gestures can better help artists better predict the gesture interaction environment. The nature of the interaction between users and algorithms will affect the usability and usefulness of these algorithms in profound ways (Fiebrink & Caramiaux, 2016). Therefore, gesture recognition for interactive machine learning systems can be used to classify and capture gestural movements through gestures to control tangible content in an intangible way.

2.3 Visual arts involving ML in different fields of creation

Currently, artworks generated on computers through machine learning algorithms largely depend on the creative input of programmers. Throughout the process of creation of the work, the ML algorithm independently makes decisions related to the appearance of the work based on the data provided by the programmer (Andres, 2017). For example, in the field of music, Qosmo uses neural networks and machine learning to combine human and algorithmic DJs to create new compositions, perform live versions of musical ensembles, and use ML motion tracking and deep learning to measure the mood of the live crowd and change the music accordingly. (Purva, 2019). In the field of painting, machine learning algorithms can predict the painting style and fictionalize the painting content by analyzing the quality of two images, making the pictures recognizable. Style transfer refers to the process of applying these qualities to another picture. The most common style transfer application is the transfer of Van Gogh's "Starry Night" style to any photo.

A prerequisite for the deeper development of machine learning in the arts is to make the technology accessible to artists and audiences. This is where technology applications need to take into account the level of involvement of ML. The visual art presented above was created with the full involvement of ML. When the involvement of ML is reduced and it is allowed to act as a behind-the-scenes worker for the artwork, a large amount of data is input to train the algorithm to generate a series of images or text, and the mechanism of creation within the work is determined by the artist, with the viewer not interacting with the work in any way as the object of the artistic content presentation. For example, using a machine learning image recognition library on the open source platform TensorFlow, the AI system learns to distinguish images of flowers (Chen, Shidujaman, Jin & Ahmed, 2020). After continuing to reduce ML engagement, in addition to all the features mentioned above, the artist can select a small number of datasets to train to allow the viewer to interact with the work indirectly in the artist's path. For example, CannyAI creates a video dialogue replacement that uses neural rendering to construct a scene representation of the face. Allowing the artist to change the way the face looks and moves without having to create a full digital person. Collaboration with IML in art practice has increased significantly as artists' involvement in theML field has increased. Computers began to transform the artistic experts who created the artwork into catalysts for creativity (Cornock & Edmonds ,1973). It follows that good design of interactive systems can facilitate the creation of visual art.

2.4 Chapter Summary

This chapter reviews the current state of machine learning in the visual arts and the field of research in gesture recognition to inform design decisions and the construction methods chosen prior to the development phase of a project. This will ensure optimal visual arts practice in interactive machine learning systems, which is the focus of this paper's research. It will also serve to compare and analyse the impact of different gesture interactions on the visual arts.

Meterial and Method

This chapter will present the design decisions and construction methods of the project, including further research into IML and gesture recognition in the visual arts.

3.1 Principles for the construction of visual art in images

In the age of digital new media, combining machine learning techniques and human-computer interaction has become a new way of presenting visuals. It is important for artists to choose the type of visual art to be used as output for application in machine learning algorithms and to produce the best achievable results. Visual art is used for aesthetic purposes in various disciplines, and machine learning has been investigated in the areas of prediction, classification, evaluation, generation and recognition for different visual domains such as images, painting, architecture and games (Santos, Castro & Rodriguez-Fernandez , 2021). Among these, the visual language of images and the appearance, method and style of presenting information is the basis for studying the type of terminal output, and it is therefore the preferred type of terminal realisable visual art for project research.

In order to achieve the best visualisation of images, it is most important to understand the basic design elements and the principles of their use, which are often used creatively by artists and designers. Good visual interaction and experience design will bridge the worlds of visual design, information presentation and usability with aesthetics (Watzman, 2001), and Arnheim states that 'vision is not the mechanical recording of elements, but the understanding of important structural patterns' (Arnheim, 1974.). The analysis of visual structure, which includes unity, balance, rhythm, focus, proportion, contrast, movement and repetition, is a necessary principle for good presentation (Demir, Cekmi, Yesilkaynak, & Unal, 2021). On the other hand, visual combination is also an important principle to use. It combines visual structures with parts of perceived similarity, proximity, continuity, closure, as well as graphics and backgrounds into a holistic visual effect (Demir, Cekmi, Yesilkaynak, & Unal, 2021).

A growing number of fields use computers for visual analysis, by integrating various computational methods to analyse visual aesthetics. These include style classification and recognition - for identifying artistic paintings; discriminating images and paintings - for exploring indicators of complexity; emotion recognition - for interpreting works with positive or negative emotions; visual aesthetic analysis - to gain insight into the attributes associated with aesthetically pleasing images; exploration and discovery of art with creative characteristics - original ideas formed at the human level, etc. (Boukhelifa, Bezerianos, Tonda & Lutton, 2016).

In summary, design principles regarding aesthetics are as important for artists as they are for computers to construct models of visual systems. Therefore, analysing design elements and design principles is a fundamental approach to successful visual art.

3.2 The language of gestural interaction

Once the input algorithm corresponding to the gesture recognition art output type is in place, IML needs to provide example interaction design scenarios. This means that the interactive system can be trained based on the gestural inputs and the corresponding labels. Gesture is an important form of human-computer interaction and when gesture recognition is used in the field of art, the artist's aim is generally to elicit positive reflection in the viewer through gesture and content, therefore the construction of meaningful visual artworks requires an analysis of the relationship between gesture and specific thought actions based on the language of gestural interaction.

The main goal of gesture recognition research is to create a system that recognises specific gestures and uses them to convey information or perform device control (Butalia, Shah & Dharaskar, 2010).HCI researchers assess the language of gesture based primarily on psychological and sociological knowledge, thus providing information about the effectiveness of the technology in achieving certain intended goals. Artists, on the other hand, take a more subjective and interpretive approach, i.e. discussing interaction scenarios in situations where there is not necessarily a job or task to be performed. For example, users categorise real-time gestures to match emojis, in order to visualise emotions in web conference communication. The language of gestural interaction is established in the context of gesture-specific, active engagement work. For the participants, the pleasure of using through gestures generates a flow of ideas around the possibilities of interaction, extending the technology employed. In an IML system, gestural classification can be interactive, allowing the user to edit the system until they get the classification results they want. The most appropriate ML model can be selected in gesture classification based on the information about the ideas reflected in the gestural interaction language studied (Trigueiros, Ribeiro & Reis, 2012). Although sometimes a focus on technical interaction delays emotional engagement, gestural interfaces that can be continuously interacted with eventually elicit heightened emotions.

3.3 Interactive machine learning systems

Interactive machine learning systems can provide guidance to artists, designers and others in the creation of art. Before building artworks using IML, it is important to think about how such a system can be constructed to present information and facilitate interaction. It is important to learn the structure of an IML system and to break down its behaviour.

The IML system has four key components, user (artist), model, data, and interface. The user drives the process by providing feedback and guiding the model training; the model is the component that needs to be trained; the data is the pre-existing model on which the model training is based; the interface is the bridge between the user, the model and the data, and provides the basis for interaction (Dudley & Kristensson, 2018). The user (artist) is the component that this article focuses on and the main driving force of the IML process. If the artist does not have a deep understanding of machine learning technology, then there is no interactive language to enhance the emotions of the participants. Therefore, users of the IML system need to have relevant expertise in data interpretation and model output. The model obtains input and determines output based on the data concept that the user is trying to train. The data description can indicate how the model responds to some output (Dudley & Kristensson, 2018).

Not many IML system tools have been built and applied specifically to the arts; ConvNet Playground is an interactive visualisation tool for convolutional neural networks. wekinator is an interactive machine learning toolkit based on Weka, which is used to prepare many musical performances as well as for user-centred design research.

3.4 Chapter Summary

As a further study, this chapter describes the choice of image visual art and gesture recognition for design decisions and the system structure and use of IML, including the general IML structure, behavioural models and tool selection. This section contains an assessment of the challenges that may be encountered in the creative process and a research and analysis of them. The next chapter presents an iterative process for the technical implementation part of the project, summarising the experience and outputting the results.

Result

According to the research carried out in this paper, the recognition of gestures in machine learning, complete with interaction effects between graphic visuals and gestures, requires the simultaneous consideration of the interaction operations of IML and the interaction language of gestures. Thus two alternative ways of interacting with gesture recognition in visual art are obtained. One is to match the corresponding visual information based on the classification of recognised gestures. The second is to track the gesture position in real time and map the movement trajectory as an image in the visualisation program.

The final decision was made to practice gesture classification. The reason for this is that gesture classification needs to be trained autonomously in the IML system for classification, and its execution can combine both IML interaction and gesture recognition interaction. The output in this case is a GUI parameter, a visual image with gui-adjusted parameters, developed on the basis of the openframework. The control of the visual image is defined as 4 different aspects countX, stepX, twistX, Scale. the input is the gesture detected by handpose.osc gesture recognition, which is made available to the wekinator by 23 different parameters and normalisation. using the wekinator as an interactive machine learning system. It learns the selected gesture and performs the trained output. The communication between these three components is based on OSC signals.

During practice it was noticed the fact that gesture recognition does not refer exclusively to gesture interaction, its interactive experience is mainly reflected in the process of inputting trained outputs in the IML system. Several aspects of IML have been validated by previous research and practical results together.

1. IML systems rely more on an understanding of human-computer interaction. To accommodate the use of non-technical experts and to help make appropriate decisions based on the user's data history, interactive machine learning requires user interface methods and intelligent systems in which the system learns new behaviours by examining usage data to improve accuracy and requires the user and system to interact with each other in order to guide the user to make correct predictions.
2. Gesture recognition applied to the visual arts makes it easier to exercise creative control over motor interaction. Graphic visual design is in principle not entirely suitable for gestural interaction, rather content that is collaborated through the body is better suited to gestural control, for example: musical instruments, games, lighting, etc.
3. The performance of gesture recognition for interaction in the visual arts depends on the accuracy with which the artist trains the model. This is because many of the states of the trained models are unstable due to the influence of the input values. The accuracy of the model should include an accurate definition of gesture classification and a model that achieves the desired effect after multiple training sessions (Wachs, Kölsch, Stern & Edan, 2011).

Discussion

This practical study of gesture recognition and visual art in IML shows how gesture recognition can be combined with visual art and demonstrates through practical results the need for IML in the field of visual art.

5.1 Combining gesture recognition with visual art

There are two different approaches used to differentiate gesture recognition, one is to obtain parameters using 3d information from key elements of the body part such as the palm of the hand or finger joints. The second is direct interpretation based on still images or existing videos. Using key elements of body parts makes it easier to classify gestures by capturing their movement. A visual image with different variations is drawn through the interaction language described. Gestures recognised in static images do not assess the temporal evolution and variation of gestures and can reduce the potential for expressive interaction and thus emotional intensification.

5.2 The potential of machine learning in the arts

Machine learning brings innovative mechanisms to the arts, allowing creative people to explore a wider range From images to film to music. In the context of ML, artists are using IML as a core medium to give visual art a more distinctive character. In addition, machine learning engages the audience in the aesthetic process of art. It is increasing its ability to create visuals by learning visual aesthetic analysis, and machine learning possesses certain remedial characteristics, and its remedial processes are viewable in detail by the viewer.

5.3 The need for the use of IML in the visual arts

The quest for aesthetics in the visual arts is to understand visual structures that allow for a relatively free formal experience (Santos, Castro, Rodriguez-

Fernandez, 2021). Using IML to analyse visual aesthetics in a variety of computational ways allows its artistic content to interact with the viewer; IML can also reduce the technical workflow in creation and increase productivity.

The project still has important work to do in terms of achieving expressive visual interaction with gesture control. Gesture data is acquired and classified according to the acquired gesture data, and different gestures are matched to different parameters that control the graphical changes. The visual graphics part is limited by technology and does not allow for the full application of visual art design principles. If IML were available to adjust the image parameters to predict the visual change in the graphics, it would result in a completely different interaction experience.

This study as a practical result, further confirms that the interactive performance of gesture recognition in art depends on the creative thinking expressed by the artist, the use of technical materials and the visual aesthetic judgement. The emergence of interactive machine learning tools has brought new tools and creative mediums to artists and changed their knowledge architecture. Practices such as gesture recognition can bring new perspectives and ideas to creative practitioners, while helping them to enhance their artistic practice and explore broader disciplinary areas. This work will continue to investigate the interactive properties of gesture recognition in different fields in the future.

Conclusion

The application of gesture recognition in the arts is dependent on the performance of the interaction. The form of interaction can be defined through the IML system. An artist creating an interactive machine learning visual artwork needs firstly an understanding of IML and secondly an understanding of the existing research areas in gesture recognition in order to be aware of the opportunities for the development of gesture recognition algorithms in the field of visual art. By researching the current state of machine learning applications in the visual arts, the need for the use of IML for visual arts applications is analysed. A comprehensive literature study and background research is a prerequisite for practising the way gesture recognition interacts with visual art.

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