Entertainment Computing: Past, Present, and Future

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Abstract

Digital entertainment is strongly associated with digital marketing and a combination of industries and media, which all need to develop and exploit creativity and innovation in entertainment computing. The research field of entertainment computing addresses all aspects of creating, designing, building, and analyzing the usage of interactive devices like smartphones and tablets, not only for playing and entertainment. These aspects include human-machine interfaces, software applications, robots, artificial intelligence, interactive television, interdisciplinary studies on serious games, digital art, edutainment, entertainment ethics and sociology, and others. In this chapter, we focus on the history of the entertainment computing field, particularly in two crucial subfields, namely artificial intelligence and games and computers in art production. In the first case, entertaining applications, including artificial intelligence solutions, are developed to compete with humans and among themselves. In the second case, advanced interaction techniques are studied and developed, foregrounding digital arts and culture's aesthetic nature and purposes.

Keywords

Artificial intelligence · Art · Challenge · Chess · Computing · Deep learning · Entertainment · Generative adversarial networks · Incongruity · Interaction · Flow · Game · Play · Style transfer

Introduction

The upcoming research field of entertainment computing (EC) addresses all aspects of designing and building the most advanced interactive systems and devices for playing and entertaining. These aspects cover human-machine interfaces, networks, robots, artificial intelligence, interactive television, interdisciplinary studies on serious games, digital art, edutainment, entertainment ethics and sociology, and many more (see also Nakatsu and Rauterberg [2011]). The scope of each field spans from fundamental theories to enabling technologies and advanced applications to philosophical, psychological, and sociological reflections on those.

According to Statista (O'Dea), in 2022, the number of smartphone users worldwide is 6.648 billion, meaning 83.72% of the world's population owns a smartphone and maybe a tablet/or computer. On the other side, 14.28% of people in the world physically cannot own a cell phone (Turner 2022). People use these mobile devices to communicate, but most of the time to entertain themselves. Entertainment is from the Old French word *entretenir*, meaning roughly "keep in a good state": *when you entertained a guest, you were keeping them happy*. Entertainment is an essential part of our everyday activities. When we are children, we play with our friends and listen to stories our relatives tell. These experiences are the basis of our ability to communicate, discuss, and negotiate with others. In his book *Homo Ludens*, Johan Huizinga showed that playing is the basis of our culture (1949). In human history, however, entertainment has been thought of as a marginal activity of lesser importance than other activities such as education, work, medicine, etc. (see also Rauterberg [2004]).

History

Thanks to the development of digital information and communication technologies, a plethora of new and interactive entertainment systems and products have emerged: from lean-back consumption (e.g., watching TV) to lean-forward interaction (e.g., playing computer games) (Haupert 2006). The younger and more mature generations enjoy playing video games, communicating via social networks, and using new enhanced entertainment media like interactive television or immersive virtual reality systems. These new systems and products are blurring the distinction between work and play, just as the psychologist Mihaly Csikszentmihalyi indicated in his flow theory (Csikszentmihalyi 1990). Rauterberg (2004) studied the continuum of play/work from a technical and cognitive viewpoint.

To make Csikszentmihalyi's flow theory (Csikszentmihalyi 1990) practically available to game development, we must balance the level of challenge and level of skills continuously during the gameplay, see Fig. 1. To achieve this, Rauterberg (1995) developed a theoretical *information framework* for learning systems based on the difference between internal and external complexity, called *incongruity*. First, he developed a measure of cognitive (i.e., player's skill level) and task (i.e., game challenge level) complexity (Rauterberg 1992). This framework defines incongruity as the difference between cognitive (i.e., internal) and task (i.e., external) complexity. Then, in an empirical study investigating different cognitive complexity measures, the special software, the *automatic mental model evaluator* (AMME), was developed to automatically analyze the empirically recorded log file data (Rauterberg 1993). Rauterberg collected many log files representing different task-solving processes automatically, hence *objectively*. The automatic analysis allowed Rauterberg to analyze these log files in a reasonably short time to run inferential statistics on the outcomes of a sufficiently large dataset. Without such

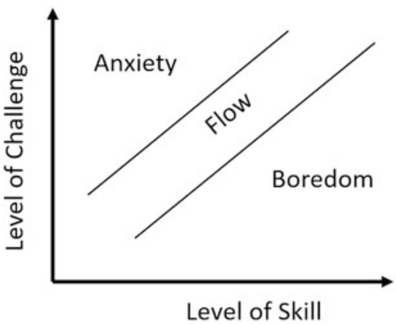

Fig. 1 The flow state is based on a player's balanced level of challenge (i.e., external) and skill (i.e., internal) (Csikszentmihalyi 1990, p. 74)

mechanical support, analyzing just one log file takes several days or weeks (Ivory and Hearst 2001).

Several approaches from the literature to quantitatively measure complexity were considered and discussed to validate a measure of cognitive complexity based on observed behavioral data. Finally, the application of the selected metrics was compared and statistically tested against the results of the empirical data. First, the complexity metric of McCabe proved to be the most effective and plausible measure of *cognitive complexity*. Second, we can mechanically specify and measure the difference between external (i.e., game challenge level) and internal (i.e., player's skill level) complexity. Commercial games possess various methods of game balancing, challenge control, and response (Aponte et al. 2011). Each modifies the game's entertainment value for players of different skill levels (Lankveld et al. 2008). The work of Lankveld et al. (2009) deals with one of them, viz. a way of automatically adapting a game's balance based on the theory of incongruity (Rauterberg 1995). They tested their approach on a group of players who played a game with different difficulty settings. The idea was to maintain an optimal incongruity automatically. They tested their concept extensively and found that the results supported Rauterberg's *theory of incongruity*. For a more detailed discussion of game design, see Crawford (1997) and Schell (2015).

Organizational Embedding

The entertainment market is vast; the companies offering products in playing consoles, intelligent toys, online games, digital music, interactive TVs, movies, robots, etc., are economically very relevant. However, until recently, entertainment beyond playing chess was not considered an important research topic in mainstream science. In the first decade of the current twenty-first century, some pioneering researchers working in entertainment met several times at specific conferences and agreed to define a new research area called *entertainment computing*. In this new area, various types of interdisciplinary research should get together. An international task force group approached the International Federation for Information Processing (IFIP) to propose a new technical committee focusing on entertainment computing. In 2002 this proposal was accepted by IFIP, and a new group called the Specialist Group on Entertainment Computing was formed. In 2006, this Specialist Group was upgraded to the official Technical Committee on Entertainment Computing (IFIP TC14). Members of TC14 have been working in various areas of entertainment computing and have been promoting academic activities in this area (see also https://ifip-tc14.org/).

Since then, several conferences and new communities have been established (e.g., Game Developer Conference, Games and Learning Alliance Conference, IEEE Conference on Games, ACM CHIplay [Nacke et al. 2016], and many more; see also [Lowood 2014]). All these events demonstrate the viability and promising future of this field.

State of Art

Today the design of digital games exploiting entertainment technologies has been recognized as an essential and attractive topic in academic research. Many people in academia and industry want to know the most recent issues and developments. Therefore, the three authors of this chapter decided to edit a handbook on entertainment computing. This handbook contributes to the prospering development of entertainment computing in academia and industry (Nakatsu et al. 2017). The prime aim of this handbook is to serve as a critical reference work as it provides the readers with a holistic picture of this interdisciplinary field, covering technical issues, aesthetic/design theories, and sociological investigations. The handbook includes invited contributions from top-class scholars and researchers from several topical areas. The editors assigned each author to recall the foundations of a specific subject in the field of entertainment computing, surveying the current state of the art in the same area, and finally sketching the most advanced entertainment applications related to that field. The sections of this handbook of digital games and entertainment technology are:

1. *Artificial intelligence and games*: Artificial intelligence (AI) is a fundamental enabling technology for improving the playing experience in several types of games. This section includes four articles dealing with algorithms and technologies for solving games, primarily based on machine learning from large sets of playing data.
2. *Brain-computer interfaces and games*: The direct exploitation of the brain activities of players (BCI) is a radically new way to interact with entertainment products. This section includes six subsections describing how special devices allow playing in novel ways and how they influence the design of modern video games.
3. *Entertainment games*: Digital games are the core of entertainment computing. This section includes four subsections on different types of video games exploiting various entertainment computing technologies. Especially a survey on the digital game industry gives readers the latest and deep insight into this fast-moving area.
4. *Interactive storytelling*: Storytelling is an ancient activity; interactive storytelling is based on software that supports a narrative whose storyline is not predetermined. Interactive storytelling fulfills an old dream: the ability of the listener to “enter” the story she is told. This section includes five subsections that display a very interdisciplinary panorama on this subject.
5. *Networking in games*: The global availability of the Internet and the widespread diffusion of powerful smartphones and personal computers allow millions of people to play anytime, alone, or at large parties. As a result, entertainment systems need advanced network technologies which connect devices with very different capabilities. This section includes five subsections on the central issues in networking for entertainment.

6. *Serious games*: Serious games are one of the most promising areas in bridging the gap between enjoyable play and professional use through gamification. This section includes three subsections: serious gaming regarding science, technology, engineering, mathematics, corporate identity, ethics, privacy, and trust.
7. *Art and entertainment*: Entertainment computing aims to combine technology with other areas such as art, culture, etc. Digital arts are novel forms of expression that we are learning to appreciate. This section includes seven subsections showing various examples of how entertainment computing handles art and culture.
8. *Edutainment*: The combination of edutainment and entertainment technologies – called "gamification" – offers new possibilities to educators and learners to understand and design new applications. This section includes two subsections.
9. *Entertainment robots*: Robots are just starting to coexist with humans in several fields. Playful robotic devices offer new challenges in human-machine interactions and enable new user experiences that need to be studied with special care. This section includes four subsections.
10. *Interactive television and online experiences*: Digital technologies enable new ways of interacting with old media: Interactive TV is one prominent example where the viewer is allowed to participate in the TV experience. This section includes five subsections.
11. *Social and ethical issues*: Because entertainment products have a technical and economic impact, and an enormous societal impact, this section addresses all related topics. This section includes six subsections: Social and ethical aspects of positive and negative effects, particularly addiction, emerging media technology, and unconscious emotions.

For more in-depth discussions on all covered topics, we strongly recommend the reader to look at this *Springer Handbook of Digital Games and Entertainment Technologies* (Nakatsu et al. 2017). In addition, this chapter here updates the recent issues on artificial intelligence (AI) and games, and art and entertainment.

AI and Games

Introduction

The *challenge* is an important aspect of entertainment (Csikszentmihalyi 1985). *When I play a game with adversaries and obstacles, I am challenged to solve problems and find solutions. When the challenge is won, I may experience a sense of gratification and accomplishment, especially if I get a reward.* This kind of entertainment is typically associated with board games, which offer many complex problems to solve.

The first element of the list in section "State of Art" – and the first section in the *Handbook of Digital Games and Entertainment Technologies* – is "AI and games." The use of AI algorithms and techniques in game design has facilitated the creation of intelligent opponents, allowing players to face challenging and strategic adversaries. AI-powered opponents can analyze player behavior, predict their actions, and adjust their strategies, fostering a more competitive and immersive gaming environment. AI adopted early board games as an experimental domain. The reason is that some board games, like tic-tac-toe, checkers, Chess, or Go, follow a small set of easily programmed rules. In addition, they offer varied challenges and increase the strategic complexity of the size of their game spaces, so they are entertaining to play. Human versus computer matches can be played for fun or specific stakes.

AI has become a key technology with significant implications for challenging board games like Chess and Go. Within the context of these games, AI has revolutionized the way programs are designed, developed, and experienced by players. Its integration into playing systems has led to gameplay, character behavior, and player experience advancements, making it a crucial area to explore in entertainment computing. Computer chess has been a fundamental research area within AI, driving the development of algorithms, search techniques, and decision-making processes. Hence, starting with AI and games with a focus on computer chess is justified due to the domain's rich history, the influential milestones achieved, and the valuable lessons it offers in terms of algorithmic development, hardware advancements, machine learning techniques, and the societal impact of AI in gaming. By examining the progress made in computer chess, we examine the transformative power of AI in game development, strategic decision-making, and the broader landscape of entertainment computing.

Chess has been a target of scientists and engineers since the end of the eighteenth century when an automaton able to play chess was shown in several European courts. It was called "The Turk" and was a hoax because, inside the machine, a human player was well concealed. Babbage also studied the problem of building programmable machinery to play chess but never made such a prototype. The first machinery able to play a subset of chess (the ending King and Rook against Rook) was built in the twentieth century by the Spaniard engineer Leonardo Torre y Quevedo (Ciancarini 1999).

The evolution of modern chess machines started with Claude Shannon and Alan Turing. They inaugurated the pioneering era of computer chess, which includes works by scientists of the caliber of Herbert Simon and John McCarthy. These people believed that studying how a general-purpose computer could play chess at the level of the best human grandmasters could pave the way to the goal of building intelligent general-purpose machines.

The history of computer chess offers a good perspective for understanding the evolution of artificial intelligence methods and technologies for entertainment computing. Chess is a challenging game, and since the Turing seminal article on the Imitation game, we assume that it requires some intelligence to play, so it has been used as a benchmark to compare machine intelligence with human intelligence (Lanz 2000). Moreover, the history of chess-playing machines is quite rich, full of historical milestones like, for instance, the famous match between Deep Blue and Garry Kasparov, the former chess world champion (Kasparov and Greengard 2017).

The impact of computer chess research on AI has been discussed; for instance, see (Donskoy and Schaeffer 1989; Heath et al. 1997). Here we are interested in its impact on entertainment computing. The following sections summarize the main milestones using a metaphoric classification of the past, present, and future research works.

The Past

The problem of programming a modern computer to play chess was introduced by Shannon (Shannon 1950) and studied by Turing (Turing 1953). It lasted until the introduction of special hardware, corresponding to the time interval 1950–1977. In 1950, Shannon described in his paper two different architectures for chessplaying software, called type A and type B programs. Type A programs systematically explore a data structure called the game tree. They are also called “brute-force” (or dumb) programs because they rely upon the available computing power to explore all positions in the game tree till the allotted time expires. On the other hand, type B programs are more intelligent because they explore only a fraction of the possible continuations, selecting them according to some heuristic and mimicking the human form of playing.

In the following three decades (circa 1960–1990), much research was invested in improving type B programs. The pioneering era focused on tree search algorithms and related heuristics. The best programs in that epoch were the Kaissa from the Soviet Union (Adelson-Velskiy et al. 1975) and Chess from the USA (Slate and Atkin 1983).

It took one generation to understand that the role of special hardware could be decisive in building a powerful chess machine. At the end of the 1970s, introducing special hardware designed for speeding chess move generation and position assessment dramatically improved the machines’ playing strength. Concurrently with advanced special-purpose hardware, which was expensive, at the other end of the hardware spectrum, some low-cost devices were introduced in the consumer electronics market, which inaugurated the new market of electronic chessboards. The Fidelity Chess Challenger was patented and introduced in 1976 (Levy and Newborn 1982).

A significant improvement in the strength of play was achieved when hardware designed on purpose for chess was introduced. This work included the study, construction, and evaluation of machinery based on particular VLSI processors organized in the architecture of massively parallel machines. This research era, roughly from 1977–1997, was inaugurated by Belle, an engine built by J. Condon and K. Thompson at Bell Labs (Condon and Thompson 1982). Cray Blitz was another unique machine based on a highly parallel architecture (Hyatt et al. 1985). Hitech was a VLSI machine built at Carnegie Mellon University by Hans Berliner and his group (Ebeling 1987). Also, at Carnegie Mellon University, a second machine was built named Deep Thought. The students who created this prototype were recruited in 1989 by IBM, and their project was re-christened Deep Blue. They made the machine that played two famous matches with the Russian Garry Kasparov in 1996 and 1997, and Deep Blue won the latter. Kasparov was then the World Champion of Chess, so his defeat was a milestone in the history of AI. The Deep Blue machine also was based on special-purpose hardware (Hsu 1999). After this triumph, developing new special hardware for chess play was oriented to exploit FPGA architectures (Boule and Zilic 2002) in combination with highly distributed infrastructures, like Hydra (Donninger and Lorenz 2005).

The Present

The improvement of computer machinery to play chess was slow but constant compared to the relatively stable human strength. This statement can be proved by looking at the Elo rating, an index used to assess the playing strength of humans and chess machines (Elo 1961).

After Kasparov's defeat several years, the best human chess players played several matches against chess programs, which concluded around 2006 when a general-purpose multicore machine running Deep Fritz 10, a standard commercial software, won a match against the human World Champion Vladimir Kramnik. Since then, no more challenges between world champions and computers have been played: the difference in the strength of the play is too big.

Software products dominate the current market of chess machines: programs running on general-purpose personal computers and implementing algorithms based on visiting a game tree became stronger and stronger as new heuristics were developed, especially to improve the scalability of a search when multicore hardware became available (Heinz 2013). Since the algorithmic structure of the chess program is well known, there is no dominant software, as incremental improvements happened continuously and were recorded by the results of the World Computer Chess Championship (Newborn 2011).

Nowadays, the software architecture of a chess program is relatively standard. There is a graphical user interface showing a chessboard, a search engine to visit a game tree, and an evaluation function over such a game tree to choose the moves to play. Programs differ in the details of the evaluation function, but their strength is generally proportional to the number of positions that can be "visited" during the search. All chess programs rely upon some opening library, and most exploit some perfect knowledge of some primary endings offered by some library. Experiments like the one described in 2014 witnessed the slow but constant progress of software chess programs (Silver 2014): Komodo 8, a program running on an Android smartphone (state of the art in 2014), was matched against Shredder 9, a program that was chess champion in 2005, running on a contemporary (at 2014) quad-core i7 processor. The match was won 5-1 by the smartphone, meaning that the software advances were much more helpful than the increase in hardware speed.

The Future

We believe that the near future of entertainment computing and AI is based on programs including some machine learning (ML) features. For instance, this approach had been attempted in the past century (Skiena 1986); however, the available hardware was not powerful enough. Deep learning, a variant of ML, showed its power in 2017 when AlphaZero running on a Google supercomputer learned to play from scratch with zero knowledge of chess data or algorithms, and playing against itself in a few hours reached a strength level so high to be able to win a match against Stockfish 8, a strong game-tree-based program running on general-purpose hardware (Silver et al. 2018). So the current trend is to run programs on multicore personal computers integrated with some GPU for running some neural network. A device with 384 NVIDIA CUDA Cores and 48 Tensor Cores that claims to reach 21 TOPS AI performance has recently been described, running the open-source Leela chess software inspired by AlphaZero (E. Zhu 2020).

Possible development for future competitions is the introduction of personas impersonating famous chess players, namely making software agents that can convincingly imitate any given human player (Świechowski 2020). These forthcoming human-like agents could be used as teachers for specific games or testers to predict interactions with human players. Another promising trend is the study and play of partial information games based on chess, like Kriegspiel, Reconnaissance, Blind Chess, or Dark Chinese Chess. Here are some general principles and lessons learned in the domain of AI and games, which can be applied to the broader field of entertainment computing:

Balancing challenge and fun: Strive for a balance between challenging gameplay and enjoyable experiences. While AI opponents should provide a degree of challenge, avoiding making the game frustrating or overwhelming is essential. Continuously monitor and calibrate the AI's difficulty to maintain player engagement.

Adaptability: Develop AI systems adapting to different skill levels and playing styles. Implement adaptive difficulty levels or AI opponents that can dynamically adjust their behavior based on the player's performance to provide engaging and balanced gameplay experiences.

Player modeling: Use player modeling techniques to understand and predict player behavior, preferences, and skill levels. This information can be used to tailor the game experience, provide personalized recommendations, and optimize the AI's responses to create a more engaging and immersive experience.

Reinforcement learning: Explore the application of reinforcement learning techniques in game AI development. Reinforcement learning can enable AI agents to learn and improve their gameplay through trial and error, leading to more challenging and adaptive opponents.

Art and Entertainment

Introduction

Entertainment can be rephrased as "play." In his book *Homo Ludens* (Huizinga 1949, p. 28), Huizinga defines play as follows: "All peoples play, and play remarkably alike." Play is a free act with no purpose, and although it does not support a person's material life, it profoundly affects a person's spirituality. People have been playing in their daily lives since ancient times. Moreover, it has created a culture and evolved people (Nakatsu 2010). Art is a visualization of the deep part of the human spirit. In that sense, art has a deep relationship with entertainment. In other words, *art* is at the heart of joy and its pure part.

Therefore, how art has been associated with computers leads to thinking about the essence of entertainment computing's past, present, and future. The author would like to think about art, especially concerning computers. With the progress of computers, computers have been used for art production since the middle of the twentieth century.

The use of computers in art production has become a method of art production and has been established in art under the names of media art and digital art. At the same time, the current trend is that AI has come to be used to generate art. Since deep learning in AI has made it possible for AI to learn the characteristics of art, it has become possible to generate images with the characteristics of art. Creating various artistic images and videos using this method is one of the characteristics of the current art trend.

The relationship between art and AI is described in this chapter. As it is important to learn what happened in the past and what is happening in the present, the past and the present of AI and entertainment will be described in sections "The Past" and "The Present". Then based on this, in section "The Future", we will describe what we have learned based on the history of AI and entertainment and what can be anticipated for its future.

The Past

The pioneers of computer art date back from 1956–1958, when the SAGE (Semi-Automatic Ground Environment) displayed a line drawing image based on George Petty's pinup art (Edwards 2013). This pinup art was the first human picture displayed on a computer screen. Then, Desmond Paul Henry invented the Henry Drawing Machine in 1960 (Anonymous 2022). His work was exhibited at the Lead Gallery in London in 1962. This exhibition means machine-generated art has acquired the right to open a solo show. Until the mid-1960s, most people involved in creating computer art were engineers and scientists who could use computers only available in laboratories such as universities. Then many artists gradually began to use computers as a new creative tool.

Interestingly, the technical institutes were deeply involved in computer art in the early times of computer art. One is Bell Labs in Murray Hill, NJ (Gertner 2012). Bell Labs was founded as a research institute that studies essential technologies related to communications and is famous for producing many Nobel Prize winners. At the same time, Bell Labs was eager to establish an interdisciplinary research area between art and technology (Noll 2016). In the summer of 1962, at Bell Labs, Michael Noll programmed a computer to produce visual patterns for artistic purposes (Noll 1994). Bell Labs continued to hire artists and worked on computer-based art based on the collaboration between artists and researchers.

Two early computer art exhibitions were held in 1965. Generative Computergrafik was held at Technische Hochschule in Stuttgart, Germany, in February 1965 (Taylor 2014, p. 31), where Noll had joined with fellow mathematicians Frieder Nake and Georg Nees to produce this first exhibition in Europe. Next, Computer-Generated Pictures was held at Howard Wise Gallery in New York in April 1965.

In 1968, the Institute of Contemporary Arts in London held a computer art exhibition called Cybernetic Serendipity (Taylor 2014, p. 43). This event is among the most influential in the early computer art exhibitions. Exhibitors at the show include Nam June Paik, Frieder Nake, Georg Nees, A. Michael Noll, John Whitney, Charles Csuri, and others who later are considered the first digital artists.

Another technical laboratory that has contributed to the development of computer art is the Xerox Palo Alto Research Center (PARC) (Harris 1999). PARC developed a graphical user interface (GUI) in the 1970s (Jansen 1998). Xerox also commercialized the Xerox Star workstation (Johnson et al. 1989), which has the world's first GUI as its primary function. Unfortunately, the workstation was not popular because it was too expensive. However, their effort did not fail and was taken over by the company Apple. Steve Jobs visited PARC in 1979, and he quickly saw the advanced GUI and started developing GUI-based computers at Apple. Based on that, the first Macintosh was released in 1984 (Associated Press 1984), and after that, the GUI became widespread. Many graphic designers quickly embraced its ability as a creative tool, and GUI is now becoming a popular essential feature of user interfaces.

Another major digital art trend was interactive art's active movement (McIver Lopes 2001; Chen 2020) from the 1980s to the 1990 s. Interactive art refers to digital art in which an artwork changes according to the interaction with the audience. The most used method of interactive art is that the computer recognizes the voice and the body/hand movement of the audience, and the image expressed by computer graphics changes accordingly. Computer graphics is often abbreviated as CG or computer-generated imagery (CGI) in the context of film and movies, as computer-generated imagery (CGI). One of the reasons this became popular from the 1980s to the 1990s is that computer advances have made it possible to recognize human movements and voices in real time (Earnshaw 2017). Another reason is that CG technology has advanced, making it possible to change CG images and videos in real time according to interactions with one or more users.

The advent of interactive art means that, in the past, artworks could only convey information in one direction from the artist to the audience. However, now the audience can give feedback on the artwork. In other words, two-way communication between the artwork and the audience became possible. This development is an epoch-making invention in the history of art. Especially in the 1990s, a lot of interactive art was produced. In addition, the Ars Electronica Center (AEC) in Austria, Zentrum für Kunst und Medien (ZKM) in Germany, and InterCommunication Center (ICC) in Japan were established as venues for exhibiting these works.

Digital games, representing entertainment, have many issues in common with interactive art (Earnshaw 2017). The interaction between humans and computers is an essential feature, and another characteristic is that the images displayed by the interaction change. However, while games have become a representation of entertainment and people worldwide enjoy video games, interactive art has lost momentum. Many active artists in this field have also shifted their activities to other areas. Considering where this contrast comes from, there are two reasons.

1. Interactive art often incorporates advanced interaction techniques that recognize human movements and voices but does not always work well. On the other hand, games have enabled reliable interaction by incorporating simple means of interaction, such as keyboards and controllers.
2. Whereas games have the simple but fundamental purpose of entertainment to entertain people, interactive art could not establish a clear concept of what the interaction between art and the audience brings to the audience. If interactive art wants to entertain people, it is closer to the game's concept than art.

The Present

It can be said that the field of art using computers for art production has been established under *digital art* and *media art* (Kwastek 2013). Many artists are active in this field. Their achievements are announced at many international art exhibitions and conferences, such as the Ars Electronica Festival hosted by AEC and the SIGGRAPH exhibition hosted by ACM SIGGRAPH. Along with that, various digital art exhibitions are held every year over the world. Also, in many galleries and museums, the exhibition and collection of digital art have become common (Giannini and Bowen 2019).

On the other hand, the current new trend is that AI has come to be used in art. AI is good at simulating human logical abilities, and as described above, it has already surpassed human skills in Chess and Go. On the other hand, art production is an illogical or emotional activity of human beings, and whether AI could handle it was a big issue.

On the other hand, a method called deep learning (DL), which learns from large datasets and the outputs based on them, has appeared in AI and has come to be used in many areas. One of them is to memorize the database of the vast past phase in the field of Chess and Go mentioned above and calculate the next best move from the current stage based on it. There is a movement to apply this idea to art. In other words, it can be considered that AI learned the characteristics of artworks by letting AI process many artworks (mainly paintings) as data. *If you let AI output an image, you can output an artwork similar to the learned artwork*. A typical example is shown in Fig. 2. This research project centered on Dutch institutions is called the Next Rembrandt Project (Pickett-Groen 2018). Here, AI learns the characteristics of Rembrandt's paintings by training AI with Rembrandt's artworks. After that, when letting AI output an image, an image with Rembrandt's style is generated. As far as Fig. 2 is seen, the output image has precisely the sort of Rembrandt, and people may consider that "AI Rembrandt" has appeared.

The artistic images output by such AI has come to be brought into the art industry. Recently, a painting produced by AI was sold at a high price of around 500 thousand dollars at one art auction (Simonite 2018). As a result, the fact that an image created by AI was sold at a high price in the art industry became a hot topic.

Another topic is the proposal of a new deep learning technology called generative adversarial networks (GAN) as a recent technology (Goodfellow et al. 2014; Creswell et al. 2018). Figure 3 shows the basic configuration of GANs. GANs consist of two networks, a generation network, and an identification network. The generation network produces an image as close to the real thing as possible.

Fig. 2 A Rembrandt-style image created in "The Next Rembrandt Project" (Pickett-Groen 2018)

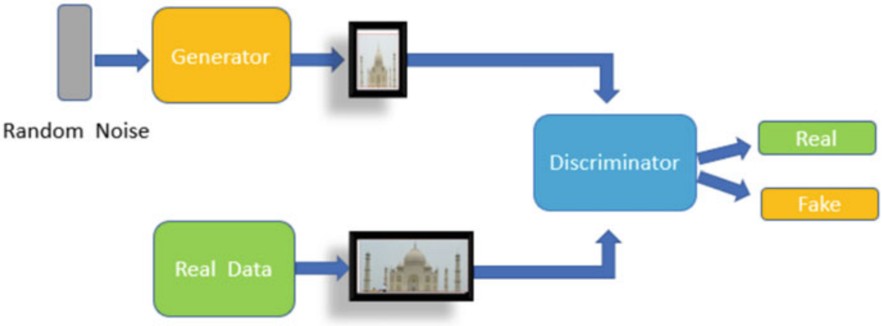

Fig. 3 Basic configuration of GANs (Shakhadri 2021)

The identification network tries to distinguish between the fake and actual images with the highest possible identification rate. Training a network with these two contradictory functions as a zero-sum game can be performed even with relatively small training data. In the case of art, a particular artist's number of artworks is not always significant, so it has not been easy to carry out AI training, but with GANs, it has become possible.

Much research has been done on GANs, and many modified versions of GANs have been proposed. As a result, using GANs made it possible to put a specific art genre or a specific artist's style on photographs. This is called "style transfer." Figure 4 shows an example of mutual conversion between photographs and Monet's paintings using CycleGAN (Zhu et al. 2017), one of the GANs.

This style transfer function makes generating images with an artistic style possible, and many images with a specific art genre or a specific artist's style are already generated (Gatys et al. 2016). It is exciting to see what direction this will take in the future.

The Future

In this section, let us consider the future relationship between computers and art. What will happen in the future? Since AI is expected to continue to advance, it is a big issue in the future whether AI will create art or not. In other words, whether AI will have its own creativity and whether AI artists will emerge will be described at the end.

Based on the earlier sections' description, lessons learned in this domain and the future anticipation for the relationship between art and AI will be described:

Use a Computer as a Tool for Art Production

Computers have been used as tools for art production since the early days of digital art. This usage will not change in the future. In particular, software that adds various

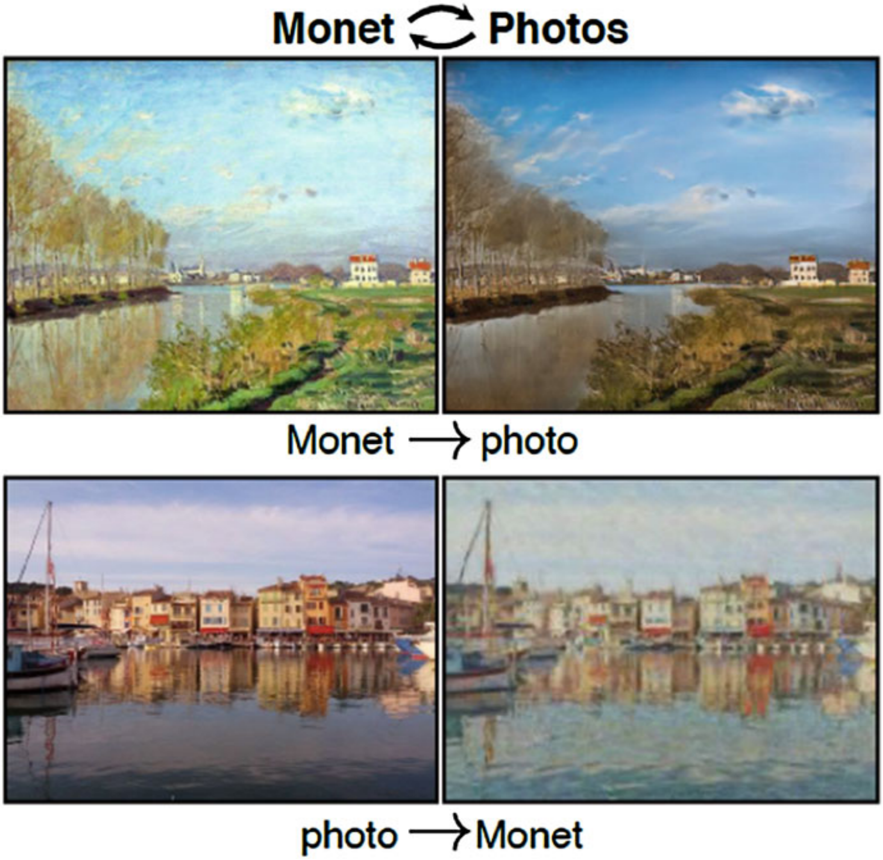

Fig. 4 Conversion between landscape photos and Monet paintings using CycleGAN (Zhu et al. 2017)

effects, such as Photoshop, will continue to improve by adding functions such as style transfer mentioned above. For example, artists can use this software to obtain inspiration for their creations by adding various effects to their artwork.

Add Art Creation Ability to the Computer

Another exciting theme is whether computers, especially AI, can have the ability to create art. It was mentioned already that AI is approaching humans in terms of human logic processing capabilities and has begun to surpass human capabilities in Chess and Go. Further, as shown in Fig. 2, generating an image with a Rembrandt style is possible. If AI proceeds further, will AI have art production ability, in other words, creativity? Ray Kurzweil predicts that AI will outperform humans in all capabilities in 2045 (Kurzweil 2005). Will this happen? We don't know yet (see the discussion in Brockman [2015]).

However, in illogical processing such as art production, it is unlikely that AI will surpass humans soon. The Rembrandt project in Fig. 2 shows that AI that learned Rembrandt's paintings can output a Rembrandt-like image. This achievement does not mean that AI has creativity. Regarding creativity, it is said that new art is born by combining what is considered completely different based on openness (Bateson and Nettle 2014). Using the style transfer function described above, let us assume a unique artistic image is born from two images in entirely different fields. Does this mean AI has created art? Instead, it was created by the person who decided which images to combine. Creativity requires a will and judgment like a human being to create meaning (Saariluoma and Rauterberg 2016). It is an entirely different issue that a computer will surpass human beings in solving a given problem and that a computer can create artwork (Lau 2011). It is not easy for computers to have creativity in that sense (Cameron 1992).

Use a Computer to Evaluate and Analyze Art

Another possibility is to use AI for art evaluation and analysis. Evaluation and analysis of art are essential issues, and various studies have been conducted. For example, figurative paintings are preferred when comparing figurative paintings and abstract paintings (Okada and Inoue 1991). Regarding the difference in evaluation between art experts and amateurs, it was revealed that experts prefer pure paintings, and amateurs prefer secular paintings (Winston and Cupchik 1992). However, in these evaluations, copies of the original artwork are used. If an original copy of a well-known artwork is used, it is easy to identify who painted it and what the title is.

Moreover, it can be easily inferred that such information would greatly influence the evaluation result. However, using the style transfer function of AI makes it difficult to identify such information. In other words, artists and artworks can be anonymized and evaluated. Evaluation and analysis research of art utilizing the characteristics of AI is being conducted (Mai et al. 2020), and research in this direction is expected to become active in the future.

Summary

This chapter discusses the relationship between humans and computers for entertainment. Entertainment covers an extensive range and describing it all is unrealistic. On the other hand, human intellectual ability consists of logical and illogical abilities. Therefore, we focused on entertainment representing these two areas, in which we discussed the relationship between humans and computers. Regarding the human logical activity aspect, board games such as Chess and Go were typical examples. Finally, we discussed how the development of computers and recent AI changed the relationship between humans and games and how it will change and further develop. Also, regarding the aspect of the illogical human ability, we took art deeply related to creativity as a representative example. And we discussed how computers and AI had been involved in the relationship between humans and art and how they will be in the future.

As discussed in the section "AI and Games" that describes the relationship between people and games, the big topic is how AI has approached and overtaken human abilities in games such as chess. In 1997, there was a significant epoch when the computer Deep Blue defeated the World Chess Champion Garry Kasparov. AI's ability has already greatly exceeded human ability in Chess, Go, and even Shogi (i.e., Japanese Chess). However, that does not mean games like chess have lost their fun. On the contrary, in Japan, AI is used as a tool for Go and Shogi professionals to improve their skills to become stronger and create new hands. Also, they are advancing into new entertainment by combining the evaluation values and optimal moves shown by AI in actual Go and Shogi games.

In the art world, AI can learn many artworks and generate images similar to the original artworks using deep learning. However, that does not mean that AI can create art. It just means that AI can generate something similar to the artwork it has learned. Instead, one direction would be to use AI as a support tool for artists' art production in the future. In addition, AI would be used as an analysis tool to analyze art history or compare Eastern and Western art. What is ahead of them? Will it be possible for computers to surpass all human abilities in 2045, as Ray Kurzweil predicts? Of course, we do not know at this point. However, what can be said is that the era of coexistence of humans and AI in entertainment will come, rather than the dystopia that people are worried about.

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