Computer Aided Creative Thinking Machines (CaXTus)

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Abstract. This article presents early-stage research and a test bed for AI technology on the integration and experimentation of creative AI (CAI) in conjunction with hybrid design tools (HDTs), environments (HDTEs) (i.e., web based), and clouds architecture. The objective is to build, develop and test HDT(E)s as assistive collaborative CAD support systems for design engineering processes (DEPs) and education. For example, in education a paradigmatic shift in the conceptualization of learning and knowledge acquisition is observed. The goal is to find a set of guiding principles, metaphors and ideas that inform the development of CAI imbued with computational support tools, new theories, experiments, and applications. Results and findings are presented of early-stage research.

Keywords: Computation, Creativity, Process, Extended Reality Artificial Intelligence.
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1 INTRODUCTION

The integration, application, testing and experimentation of creative AI (CAI) technology (i.e., unsupervised learning) in conjunction with hybrid design tools (HDTs), environments (HDTEs) (i.e., web based), see Figure 1(a) and cloud architecture, as shown in Figure 1(b) is being explored.

The objective is to build, develop and test HDTs as assistive collaborative CAD support systems for design engineering processes (DEPs) and education. For example, in education a paradigmatic shift in the conceptualization of learning and knowledge acquisition is observed.

With the advent of multimedia technology, engagement through interactivity has the potential of increasing enjoyment, and fostering new forms of creativity, social activities and learning (e.g., video teaching). The potential of artificial intelligence (AI) software that acts as a creative collaborator is envisioned. Deep Learning (DL) (e.g., convolutional neural networks (CNN), generative adversarial networks (GAN)) enables us to do things with algorithms (e.g., augmented creativity) that have never been done previously [10].

We take a holistic approach to address under-constrained problems, how computational aided creative thinking (i.e., computational creativity (CC)) and inventing machines [23] can engage "wicked problems," [4] and/or "ill-structured problems," [33] identify or reveal blind spots [42], and how to benefit from AI innovations (i.e., iterative routes to intelligence) in individual and/or collaborative creative processes (e.g., product development), shown in Figure 2(a) and Figure 2(b).

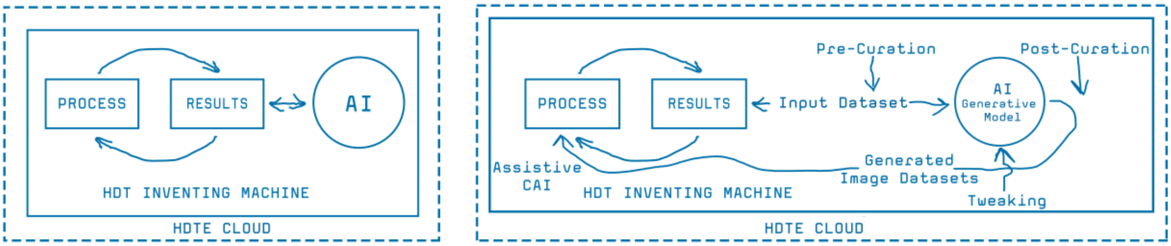

Figure 1: Typical framework HDT and HDTE with integrated AI-CNN (a) and hybrid clouds architecture HDTs (b).

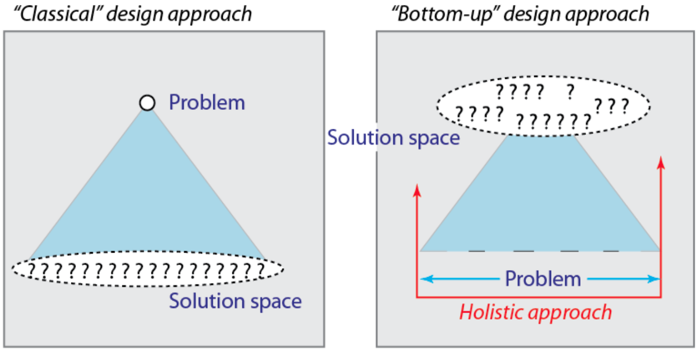

Figure 2: Problem solving with 'classical' design approach (a) and 'bottom-up' design approach to problems and knowledge with holistically structured solution space (b).

A machine, similar to the HDTs, that incorporates randomness, deviation-amplification and deviation-counteracting, may be both efficient and flexible. It can search for all possibilities. It can try to amplify certain ideas in various directions. It can stay at a relevant idea (which may change from time to time during the invention) and bring back to 'it' other ideas for synthesis (ibid.) [23].

The goal is to find a set of guiding principles, metaphors and ideas that inform the development of computational support tools imbued with CAI (i.e., CNN), new theories, experiments, and applications. Results and findings are presented of early-stage research and testing. The expansion of the possibilities of and space for activity, increases the complexity of events and thus the uncertainty of the outcome [27].

2 MAIN IDEA SYSTEM HDT-CNN, COMPUTATIONAL CREATIVITY AND ARTIFICIAL INTELIGENCE

Over the years we have made steady progress towards the inception of hardware (i.e., build) and software (i.e., develop) which creates HDTs and HDTEs for creative and conceptual purposes. We employed a variety and diversity in open-source, virgin- and processing software, video, graphics, audio and sensor techniques to achieve instruments, tools, unconventional interfaces, multi-modal interactions and systems that assist and support users (i.e., designers, engineers, architects, students etc.) in their processes [43], [44]. We refer to our main body of work in research and development of HDT(E)s for further scope, approach and foundation [36-39], [41], and [45].

To develop and build software that can be 'creative' and observed as 'being creative' is difficult and much progress is still to be made, however, our testing, findings and results point to potential 'creative thinking machines' (CTMs) that provide users valuable interactions, experiences and enjoyable creative processes and conceptualizing experiences. The inclusion and integration of AI technologies could instill and spark novel ways-of-working (WoW), increase understanding, enhance knowledge acquisition, creativity and trigger the potential of altering perspectives and perceptions of users on embedding CC and CAI.

We believe that CTMs, employed either autonomously, concurrently or fully assistive, to unify approaches, to enhance human-machine collaborative interactions (HMCI) and allow new avenues for productive purposes and interconnected directions, needs to be investigated continuously and explored fully. Or to paraphrase Ada Lovelace, that CTMs 'might compose elaborate and scientific pieces of music, art, design, recipes, creativity in ideas of any degree of complexity or extent' (*"developping [sic] and tabulating any function whatever. . . the engine [is] the material expression of any indefinite function of any degree of generality and complexity"*) [21].

2.1 Creative Conceptual, Analogue-Digital Thinking and Blind Spots

In creativity it is crucial that you produce as many ideas as possible, produce ideas as raw and wild as possible, build upon each other's ideas and avoid passing judgement [29]. The notion that machines can't be genuinely creative, at least in the literary sphere they can nonetheless be engineered to seem to be creative [4]. Obviously, this 'idea' constraints our perception and openness towards 'machines' to allow room for exploration in its future ability of 'owning' cognitive reasoning, idiosyncratic behaviour, affectively and creativity.

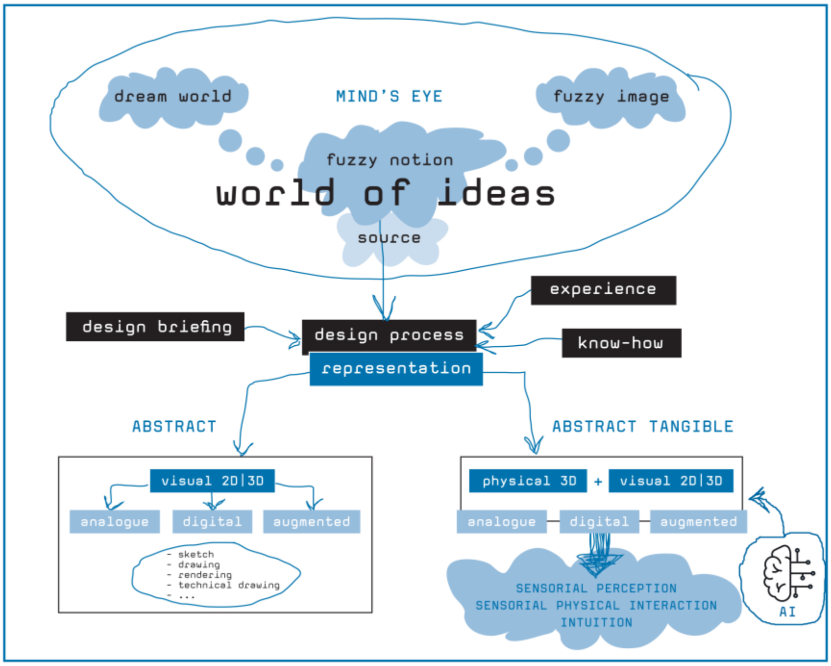

Figure 3: The HDT framework of human creative action, capacity, meta-cognitive abilities and intention based on hybridization, digitization and embedded CAI.

Creativity is a concept of individual differences, which is intended to explain why some people have higher potential to provide new solutions to old problems than others. It leads us to change the way we think about things and is conceived as the driving force that moves civilization forward [13].

The creative action and intention often entail the dynamic process of creativity unleashed during design and/or engineering processes (DEP). Our initial focus is on early stage (phases) of the creative thinking process (sometimes called fuzzy frontend (FFE)), wherein thoughts and fuzzy notions are transformed and represented, that often stem from the mind's eye (inner visions), metacognitive aspects, imagination, mental divisions and distractions, as shown in Figure 3.

We still have to define what creativity means. We know some of the attributes have to do with finding something novel, unexpected, and yet useful. While advancements in AI mean that computers can be coached on some parameters of creativity, experts question the extent to which AI can develop its own sense of creativity [2]. This early-stage research investigates and explores combinatorial HDTs imbued with CAI.

Devotion and intent are fused together to bring out ideas and fuzzy assumptions to manifest 'brain generated' content through the creative force and applied as elements in the creative act. In effect it is widely recognized that designers and engineers find it hard to ignore obvious constraints, consequently ignore blind spots and/or impediments on their imagined iterative 'concepts,' before they have been fully created and/or developed [42]. The designer, the engineer, like the consumer, is characterized by his or her experiences, beliefs, motivations, expectations, capabilities and culture, see Figure 4. For example, the designer also has some anticipation of the eventual consumer, including some intentions for how that consumer should respond to the product [7].

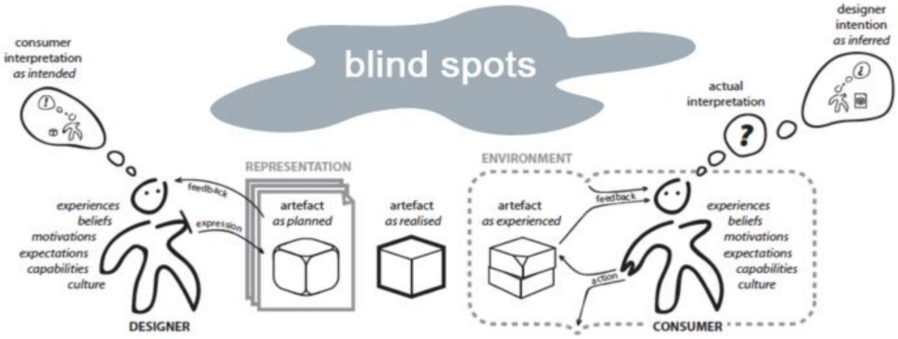

Figure 4: The friction between intention and inference: framed as apparent blind spots.

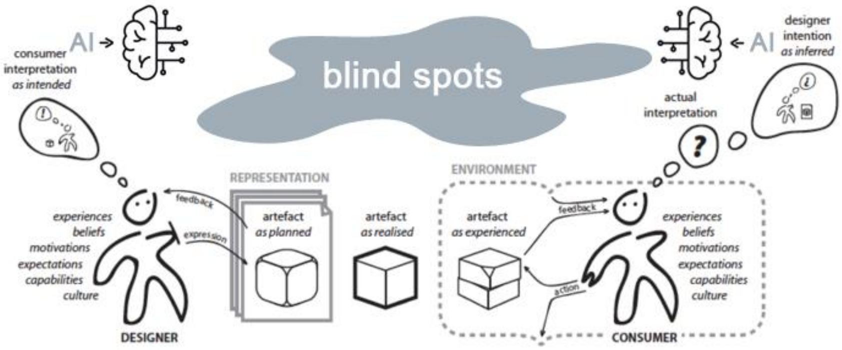

Figure 5: The friction framed as apparent blind spots imbued with AI.

Embedding AI could potentially lead to detect and identify 'blind spots' earlier and/or timely during the dynamic process of creativity unleashed during design and/or engineering processes (DEP), see Figure 5. Small errors, oversight, early in the DEP-FFE may not become apparent until much later in the process or until it becomes too late. The potential of CAI or DL technologies could be advantageous to the processes and benefit the outcomes. Robust HDT(E)s coupled and integrated robust AI (e.g., CAI) is crucial to support and assist users (e.g. designers, engineers, users) during the DEP-FFE process.

2.2 Intuition, Intention and Process

Intuition and intention are a process of thinking. The input to this process is mostly provided by knowledge stored in long-term memory that has been primarily acquired via associative learning.

The input is processed automatically and without conscious awareness. The output of the process is a feeling that can serve as a basis for judgements and decisions [1]. Intuition comes in two types; either holistic hunches, a judgement or choice made through subconscious synthesis of information drawn from previous experience and knowledge or automated expertise when judgements or choices are made through partial subconscious (i.e. autonomous, self-aware) process involving recognition of the situation [25].

Intuition in the beginning of a DEP-FFE functions as an inspirational process. It is the search for forethoughts within the user (the subject) and for objects outside of the user (in the world) that can be connected to the design problem. The more uncommon connections laid in this process are, the more creative they will become, to the extent that they are no longer understandable for other subjects. Embodied imagination (physical experiences and its structures), intentionality, and metacognition could simultaneously 'link' this imagination (individual or collaborative) congruous with the digital-virtual realms based on natural physical and intuitive interactions and explorations [40], as laid-out in diagrams Figure 3, and Figure 7.

Two thought processes or two modes of thinking are distinguished, system one and system two. System I is commonly called the intuitive system and System II the rational system. Both systems process different information and process it in different ways [16]. This lead to postulate that by embedding CAI it might be possible to connect this theorem, for example, to actual system architectures, networks and tools.

Tools support and assist designers and engineers in their daily interactions with real and virtual worlds, in conjunction with the meta-cognitive aspects and intentionality of the tool user(s). Most of our tools enable us to acquire a natural or synthetic extension of the physical and/or virtual realms and enhance the human capability and capacity in their interactions with these multiple realities, as presented in Figure 6 (adapted).

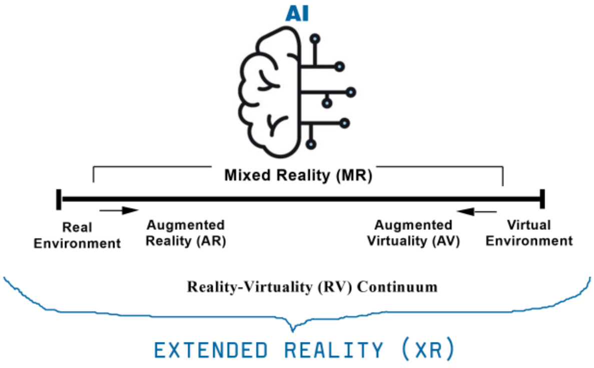

Figure 6: The Reality-Virtuality Continuum [24]: cyber-physical integrated CAI as extended reality.

To construct a tool based on perception, including embedded CAI and intention-in-action serves as a potential grounding for learning-by-doing, knowing-in-action, reflection-on-action and thinking-on-your-feet [12], [31], [41], subsequently taking full advantage of extended reality (XR).

2.3 Curiosity, Uncertainty and Unexpected Elephants

The fascination with the new, by contrast, is activated by curiosity and the desire to explore and exploit the unknown [27]. To gain this experience, curiosity uses all senses and means available to human beings. The inclusion of senses (i.e., touch, sight, taste, hearing, and smell), perception (i.e., thermo, noci, equilibrium, proprio) and tacit knowledge (i.e., experience, personality, mood, condition) be it human and/or from a 'machine,' could be in close reach with integration and deployment of DL and AI. Hence, KansAI could be an advanced function of the brain that can be the source of emotion, inspiration, intuition, pleasure/displeasure, taste, curiosity, aesthetics and creation [44].

Curiosity is a cognitive ability that the brain uses to explore the environment. To unfold curiosity's potential, the use of cognitive tools—particularly thinking, the capacity for abstraction, and the technical skills needed to produce material tools that change the environment—has to be embedded in cultural practices and anchored in a social structure. The human brain and its capacities are unique, not so much because of their biological development (which is not unique) but because of the human capacity to create and assimilate culture and pass it on to the next generation. The human brain and its capacities are the hybrid product of biology and culture [26].

The process of innovation coupled with scientific-technological curiosity, create unexpected scientific-technological breakthroughs or emergent technologies that formulate answers to societal demands and challenges for new solutions to problems. Reversal, weird, vagueness and flip in perspective is what we need to understand the creative power of things. The distinction between science and technology, between the objects of knowledge and the things that help bring it forth, is not identical to the boundary between uncertainty (which is feeling one's way toward new knowledge) and certainty (which is needed to trust that things will function).

The greater the desire for the unexpected that is brought forth by research in the lab, the more the pressure of expectation grows to bring it under control and steer it in specific directions while excluding other directions. "Don't think of an Elephant!" When you negate something, you strengthen the concept! [18].

2.4 Thinking on Thinking, Thinking Machines, Cyborg Stance

Machines cannot think, but they could perform particular brain functions described by humans at the stage of designing the machines. The machine can only do what we tell it to do, up to today machines do not possess or function with a 'mind.' One could say that a man can 'inject' an idea or insight into the machine, and that it will respond to a certain extent and then drop into quiescence, like a piano string struck by a hammer [6]. By itself, the brain can achieve little. The brain seamlessly weaves together a complex web of information from sensory systems and cognitive processes, as presented in Figure 3, Figure 4 and Figure 5. The sources of experience may be initially individual, but for experience to be usable, it must be processed by culture and the synergies that result from interactions among many other human brains [26].

"The only thing you know is, 'I am conscious.' Any theory has to start with that." [17]

An insight does not mean that the user is able to rationally explain "the big picture". User intuition could be supported and triggered by presenting him or her with objects (e.g., artefacts, glitches and thoughts) randomly or in line with objects from similar projects. This is done to facilitate the creation of (uncommon) connections and therefore evoke the inspirational process.

Therefore, rationalizing the insight is needed to communicate the knowledge with others and make it plausible for them. An opportunity would be a system imbued with AI, that supports the rationalization of the designers' insight [35], shown in Figure 1(a), Figure 1(b) and Figure 7.

GAN, for example, addresses the lack of imagination haunting deep neural networks (DNN), the popular AI structure that roughly mimics how the human brain works [10]. DNNs suffer from severe limitations like heavy reliance on quality data, whereby the training data often determine the scope and limits of its functionality. DNNs rely on large sets of labeled data to perform their functions. However, less so when used for unsupervised learning. In essence one needs human interventions to label the training data, while it takes a lot of time training the data. To generate new data, DNNs are extremely efficient in classifying things, but creating them is another thing. This means that a human must explicitly define what each data sample represents for DNNs to be able to use it.

However, if we step away from the centrality of human brains (minds) altogether and consider social complexes as distributed systems involving more or less cognitive elements. Then, we could consider the previous perhaps in terms of the mind being extended to a distributed system with an embodied brain at the centre, and surrounded by various other tools and environments, from digits to digital computers to DNNs [5], as presented in Figure 3 and Figure 7.

Machines/computers built of inorganic raw materials cannot think, but they could outperform humans doing a particular task, regardless of whether it is intelligent or not. Since machines can 'never think,' robots have no evolutionary perspective. Upscaling, enlarging, improving and continual optimization of algorithms might lead to enabling technologies that actually could built CTMs.

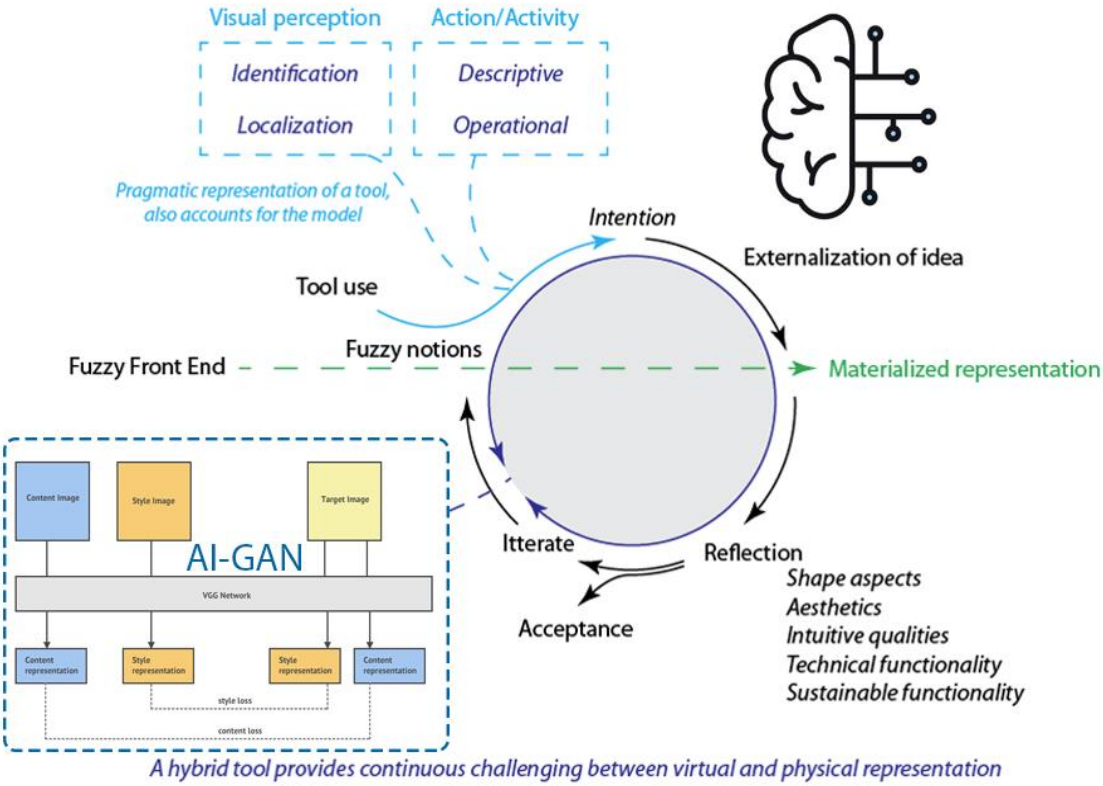

Figure 7: The continuous challenge between cyber-physical and integrated CAI representation and processes (e.g., CNN-GAN).

The real challenge is the managing of permanently evolving societies of "humans-becoming cyborgs" – the products of evolutionary symbiosis of humans and human artifacts [11]. In accordance, it is concluded that cyborgs, the products of evolutionary symbiosis of humans and human artifacts, seem to be our evolutionary perspective. The concept of 'Strong AI' - instantiating a computational machine with genuine understanding – so far did not lead to concurrence on computers/machines that can think, are affective, show empathic behaviour or have minds for that matter.

Computational theories of mind cannot fully explain human cognition or metacognition for the the time being. In principle all programs (software) are formal (syntactical, not sufficient for semantics) and minds have semantics [32]. When a computer "talks" to another computer, it's a-signifying, while when a human "talks" to another human using some language, it's signifying. For example Watsons function is answering questions [11], [14].

For now we consider, that for human problem solving, CTMs and other computational assistants or use of an information-processing system (i.e. thinking-machines, design-machines, teaching-machines) that creates problem representations and possible solve-for-solution searches selectively through rhizomes of intermediate situations, seeking the goal (target) situation and using heuristics to guide its search, could be a promising path and realistic prospective [19], [44].

The objective is the design of a machine which 'invents' [23]. A trial-and-error machine is inefficient because it has no directivity. But it has a great flexibility. A deviation-amplifying inventing machine, on the other hand, works in the direction specified by the initial kick, and, for this reason, is efficient. It is not built for any specific direction, because the direction is a variable which is specified by the initial kick. In this sense it is flexible. But in another sense it is not flexible because once the direction is set, it will persist in that direction.

A machine that incorporates randomness, uncertainty, instigate curiosity, in which deviation-amplification and deviation-counteracting may be both efficient and flexible. It can search for all possibilities. It can try to amplify certain ideas in various directions. It can stay at a relevant idea (e.g. which may change from time to time during the invention, ideation), or initial kick and bring back to it other ideas for synthesis. In fact, openness to strange hunches, weird returns, fuzzy notions, and ability to elaborate on them and to bring them back to a synthesis are what is found in the process of human creative minds in conjunction with cyborgs and machines.

3 INITIAL EXPERIMENTS AND TESTING HDT-CNN

The HDTs including CAI are XRs that allow users physical (i.e., bi-manual) tangible interaction with real-world materials, artefacts and objects, using for example, both your hands and/or your foot (feet) to capture iterative steps during the process, whilst simultaneously assisted by virtual and augmented realm and imbued with AI. The HDT(E) system use, architecture and typical framework [36-39] are shown in Figure 8 and Figure 9.

The HDTs and HDTEs are a 'workbench/-shed' approach (i.e., the active stance) for design and engineering interaction to stimulate intuition, creativity and imagination during the ideation and conceptualization process (e.g., early-stage, fuzzy-front-end). HDTs developed into intuitive and simple creative-thinking devices using video-streaming, multiple filters, web repositories and multi-modal robust interaction. The screen in front of you displays the virtual workspace. For instance, with transparent tweezers the user holds a variety and diversity in objects, drawings, materials under the camera in the sensorial space between the camera and work-surface (workbench), as presented in Figure 10(a) and Figure 10(b).

By changing the perspective on what a tool, interface or computational tool should do in order to support the human user in a certain task as an extension of his or her being, a change in paradigm could happen or spring to life. Our efforts to keep the individual human user dominant and in control of the interaction with analogue or digital realms simultaneously mix the best of both worlds resulted in a variety of hybrid design tools [36-39].

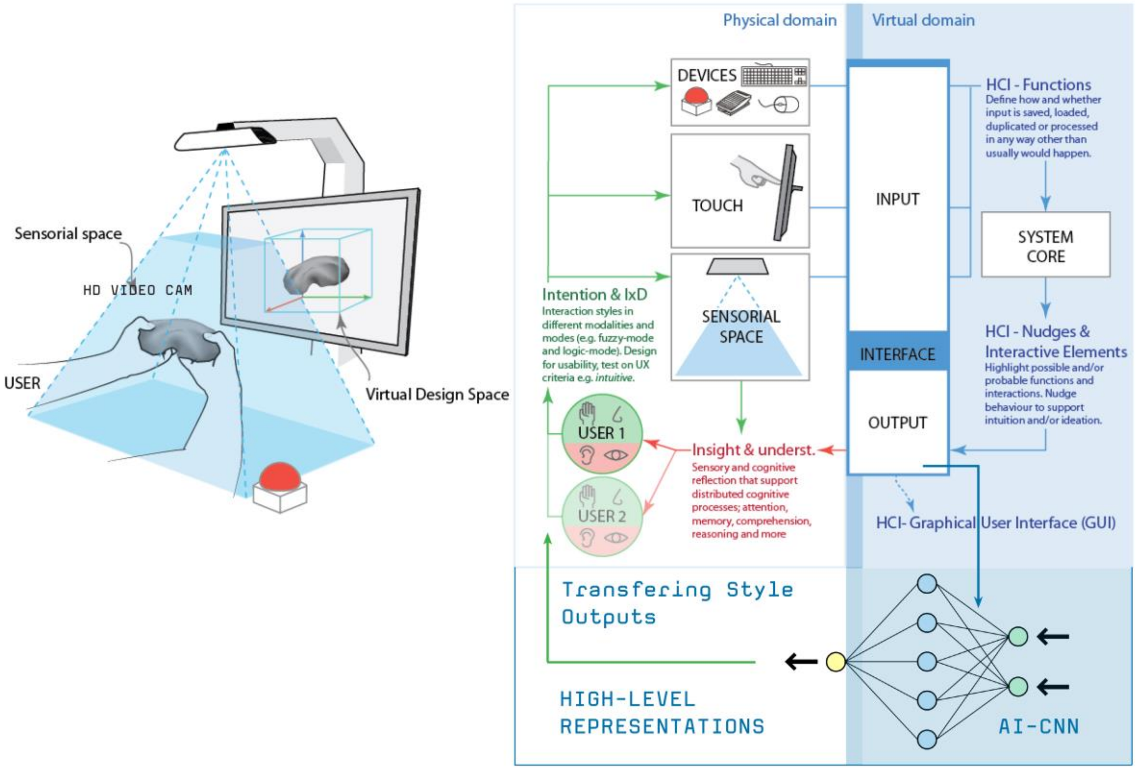

Figure 8: Typical framework HDT and HDTE with integrated AI-CNN.

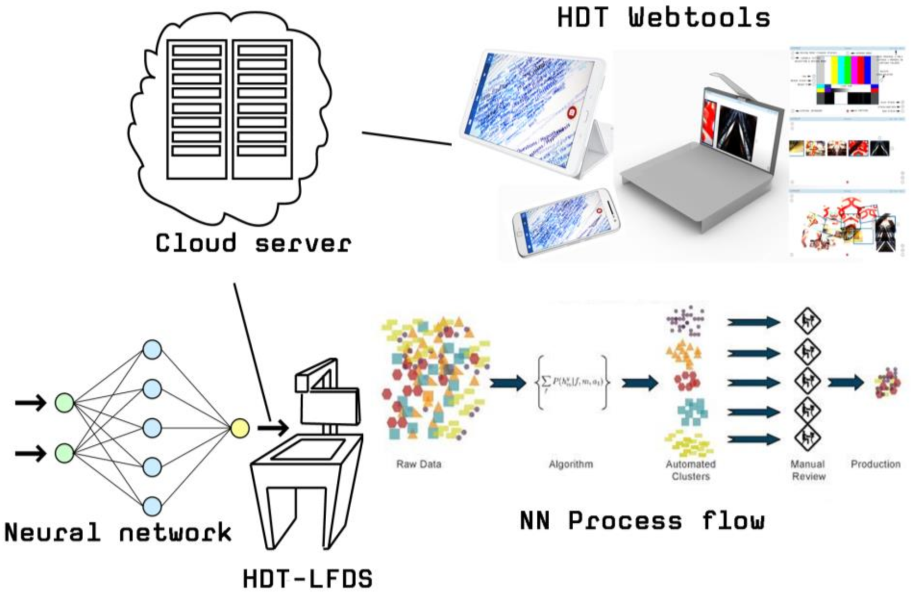

Figure 9: Typical framework HDT and HDTE with integrated AI-CNN and Cloud architecture HDTs.

Still, it is hard to believe that in a few decades we allowed so much reductionism and devaluation of the physical and visual skillsets of humans by allowing computers so much autonomy. On the other hand, the seemingly endless possibilities that digital technology has to offer awakens a healthy curiosity to find new meaning, new frontiers and invent new techniques to continue a quest for empathic and affective computational assistants.

Through interaction, designers can engage "wicked problems," gain from an added design perspective, frame design knowledge, become active in the intended approach (choice), unleash their creative potential subsequently taking a holistic approach to addressing under-constrained problems, ill-structured challenges and benefit from thinking-on-your-feet and reflection-on-action.

The combinatorial effect of cognition (i.e., metacognition, memory patterns), sensory affect, intuition, perception coupled with intention, experience and knowledge (i.e., domain) enables creative design idea generation (idea search) and conceptual design.

Standing up (i.e., your active stance is more like being at a potter's wheel than working behind a computer) during interaction enhances the experience (i.e., standing, moving, twisting), intuits knowledge and understanding of the user-interface (i.e., low-threshold and zero learning curve) and engage the user(s) in interaction with the tool functionally, productively and creatively activated semi-immersive process.

The creative thought process is founded on ambiguity to enable a multiplicity of interpretations. These mental representations of space (e.g., design space, ideation space, creative space) are constructed, however not from a single experience neither from a distinct modality. We experience 'space' from a specific viewpoint at a certain time, but nevertheless time and space are perpetually changing.

Hybrid software tools for design and creativity try to provide a simple, flexible and efficient workflow and still not limit (i.e., freeze, fixation) the creative output.

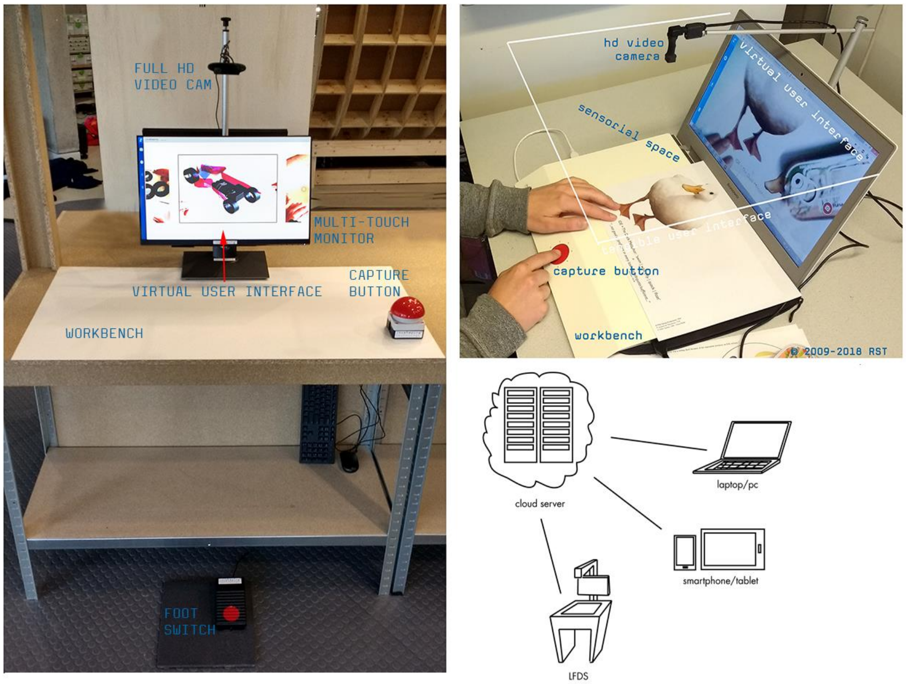

Figure 10: Typical embodiments HDT and HDTE with integrated AI-CNN (a) and cloud architecture HDTs (b).

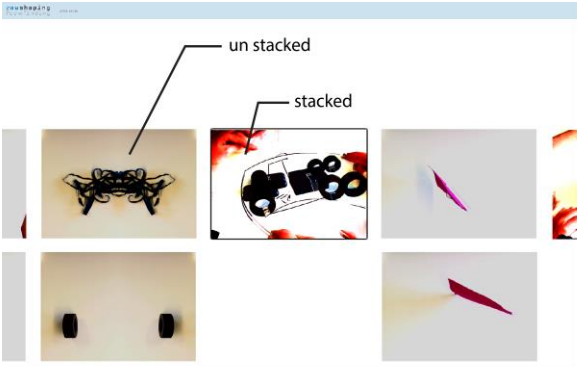

Figure 11: Multiple iterative instances are captured (i.e., instances, merges, stacks).

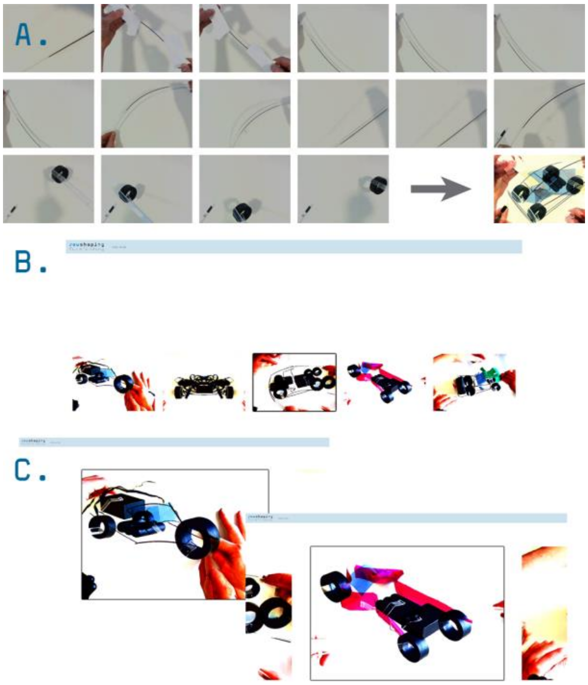

Figure 12: Generic and typical results (output) HDT generative design process, i.e., instances (a), merges (b), and stacks (c).

The multiple iterative instances are captured and frozen on the screen during the process, Figure 12(a). Combined instances can be stacked, either selectively or automated during and/or after the generative process, shown in Figure 12(b) and Figure 12(c). Computational listing and image database repository of the iterative process allows the users to access fallback choice-architecture, decision-making and make full use of the hybrid environment and design synthesis capabilities.

The output files (e.g., stacks) of the HDTs are layered instances (i.e., multilayered perceptrons), see Fig. 13 and end-results are either stacked or intermediate saved instances (in fact multiple contents resources are valid as inputs) being used as original inputs for the CNN to gain a newly generated image that serves as new input during the DEP-FFE [36-39].

Figure 13: Generic content and contextualized results (output) HDT generative process.

The user interaction input and captured content generates representation sequences and data flows in the system. The output can be re-used directly by the user to re-iterate intermediate content. If substantial iterations are captured and stored (iteration galore) the user can choose to review, select and make decisions on what to keep as possible processing results, as shown in Figure 11, Figure 12, Figure 13, Figure 14 and Figure 15.

We use the output of the HDT (raw data instances and/or stacks) to generate data (not accurate, unrealistic, creative glitch, raw artefacts) to map that towards output through a matrix of noise pixels. The approach, based on our HDT-framework, is not to gain perfect, highly realistic returns or visual representations, but to take advantage of the generated structural artefacts and distortions (i.e., raw data) stemming from the 'machine,' see Figure 14 and Figure 15.

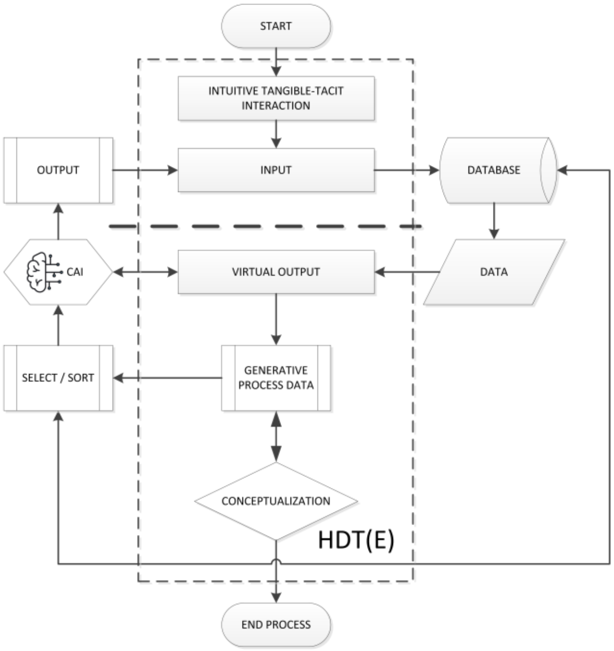

Figure 14: Generative contextualized design process HDT integrated CAI.

All the data that is generated with HDTs and/or HDTEs (instances, stacks, but also the way it's sorted and organized) can be downloaded from the data-repository (cloudserver). All the instances itself are automatically saved, including the stacks as merged images. It is also possible to directly print instances or merged instances with the HDTs.

Figure 15: Generative contextualized design process results HDT iteration galore.

Creating, orchestrating and modulating this way symbiotically during the DEP-FFE process, increases the level of iterative (i.e., iteration galore) transfer and complexity of creative interactions between human and machine subsequently "feels like" a collaborative effort. Making use of the current limitations (i.e. accept the 'weird') of GAN helps in creating insight and understanding in how CAI could become productive and assitive within real-world applications.

Synthesis is considered a trade-off between humans and machines in a given solution space optimization, whilst finding solutions for problem-based and/or set-based problem definitions, which are framed onto multiplicity of solution exploration, choice-architecture and decision-making. The assistance and support by implementation of DL algorithms allow to take two separate neural representations of two given images, and then recombine them using a DNN. In our study we deploy a CNN, which can be explained as an immense sequence of filters.

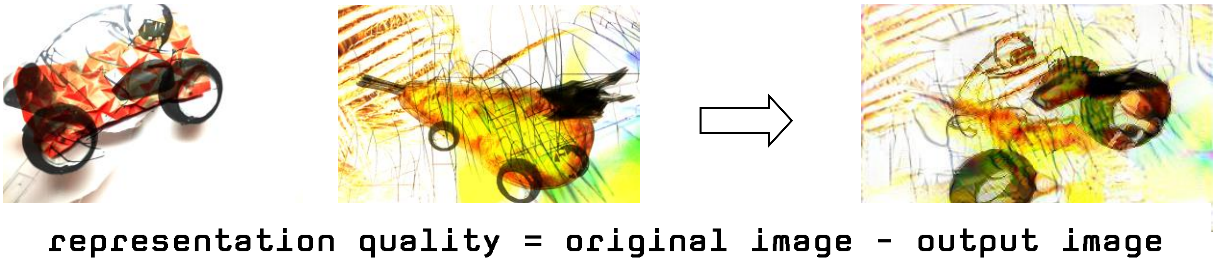

Figure 16: Outcome HDT (output) (a) and (b) used as data and GAN result (intermediate) (c).

After multiple iterations and additional modifications were applied to the shape of the network, such as, exploring the effects of a convolutional shape, which implies descending the number of neurons as the layers progress, the results became more promising. Once applied to a general image (stack), created by an HDT, as examples shown in Fig. 16, the results were already starting to look a lot more like the original input, Figure 17(a), Figure 17(b) and through Figure 17(c-d).

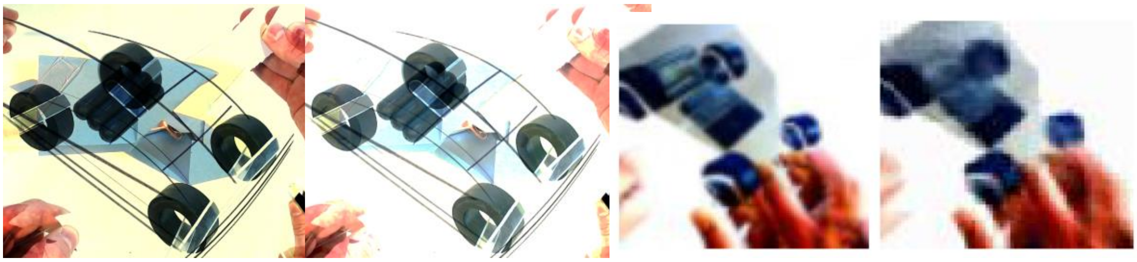

Figure 17: Left original image (stack) (a), middle image-representation CNN (b), right excerpts generative process (low-resolution and low-level features) (c - d).

3.1 How CNNs Work

CNN can be explained as an immense sequence of filters. These filters are divided into smaller batches of following filters into the various hidden layers of the neural network. A filter can be imagined as a small window of just a few pixels that scans across an image. At the start of the network, these filters are sensitive to specific shapes. If this given shape is actively present in an image, they will provide a significant output to the next filters, shown in Figure 16.

These 'shapes,' for which a filter is sensitive, will from now on be referred to as features. At the start of the network, within the first layer, these filters are sensitive to rather small features, which can be as simple as a line or an edge. Within the next layers, the shapes for which these filters give a high output will become more involved with each layer as the filters start to combine themselves to more complex forms. As a rule of thumb, the further down you go in the network, the more accurate the representation of features will be in comparison to its original input: the input image is being reconstructed layer by layer throughout, from all the edges that were detected in the first steps of the network, patched together by the subsequent layers (Figure 18).

Given that the network is large enough, it should be able to reconstruct the original image with extreme accuracy, while also being aware of what shapes are present in the picture at hand. CNNs have the ability to recognize objects or identities with extreme accuracy. This is done by extending the Network with a few, so-called, classification-layers.

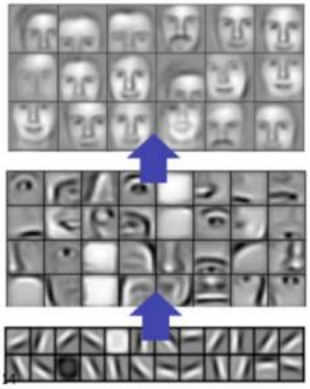

Figure 18: Learned features from a Convolutional Deep Belief Network [20].

These layers take the input that was reconstructed by the layers just-before the classification layers and measure their 'output-strength.' The classification layer then checks which neuron(s) gave a strong output, and maps this to a classification mapping: each output is matched to a particular object or identity, if the output-strength is high, then it is very likely this object or character is present within the image given as an input to the network.

3.2 Style Representation and Transferring Style

The essential trick that makes it possible in a Neural Network (NN) to learn how to recombine high-level representations all the way up from the identified lower-level features in its other layers, is through the optimization function (i.e., cost function). This function allows the network to compare its output (i.e., predictive) with the actual goal (i.e., target). The optimization function compares how close the prediction of a network is to the target, and then predicts what small tweaks need to be made to the network to improve the prediction next time. The process of prediction, comparing and finally followed by tweaking, is performed countless times until the network gives a prediction (an image-representation) that is identical to the target (the original image). This process is also called gradient descent: it is the key that allows NN to learn from their mistakes, literally.

When two images need to blend by transferring style to one another, such a simple function cannot be used anymore. Instead, another solution is provided in which two 'original' images, one for content representing the object, and one image to absorb the style, are considered as near perfect (raw) representation of the original, i.e., 'content representation' [8]. In such, the NN recreates the original style image as a 'set of lower-level style representations.'

Instead of averaging the pictures, as a result, it adapts the higher-level features of the content image to be recast using the lower-level features of a given style representation. Therefore, the style will look and feel the same as the style-representation, while the objects displayed in the content-representation will still be recognizable as the higher-level features remain. Moreover, the function attempts to reach an optimum at which the lowest minimum possible will be achieved.

Adaptations were implemented to the algorithm and these changes aimed to give the end-user more control over the algorithm's 'effectiveness' and to provide the result without having significant delays.

By allowing the network to give output as its trains, the user can already start to see what the network will be aiming for given more time. The training process makes the style representation more useful over time as the creation-process is happening. It also provides the user with the opportunity to stop the training, should the style representation become too dominant to his or her liking.

An additional modification to be implemented, is the addition of controllable parameters, to modify the style transferring-process, which the user can tweak and experiment with. These parameters serve as knobs to fine-tune the perceived depth of the style transfer, the (dis) favouring of style over content and the ability to boost the rate of learning of the algorithm for faster ('rawer') results. Weight modulation and demodulation is also deployed, except the output layers for the latter. By tweaking the weight-matrix, the resulting set of weights will be different for each sample in a batch, but will be shared among all locations in an image between hidden and visible layers [20].

The HDTs are connected to the internet and work in a browser (i.e., Chrome), it can access pre-trained models and therefore leverage their capabilities without the need of training their own network or spending significant time on training their machine-learning-models (MLM). Several test and iterations were made, before we could apply the gained knowledge and insights to the HDTs architecture and system. Additional modifications were applied to the shape of the network, such as exploring the effects of a convolutional shape, which implies descending the number of neurons as the layers progress.

The results were more promising, and once applied to a generative image created by an HDT (i.e., instances, merges, stacks) as shown in Figure 15, Figure 16 and Figure 17, the results were already starting to look a lot more similar to the original and adoptive input. The algorithm is only capable of applying one particular style to an image. By improving the algorithm to be able to use multiple sources at once, would significantly enhance its potential. Some research already suggests methods of multiple style-transfer in real-time and to improve the temporal style continuity from frame to frame [22].

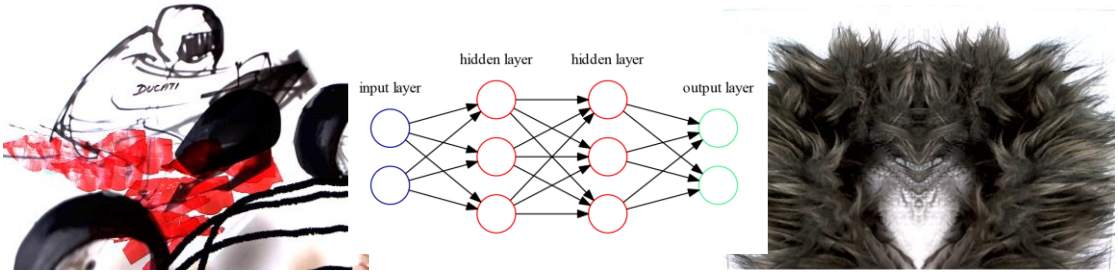

Figure 19: Style extraction and texture, left original image (a) and right insertion adoptive image (b).

The current implemented solution makes use of an algorithm that can extract the style and/or texture of one image and inserting it into another while maintaining the contents of the original image, as presented in Figure 19(a), Figure 19(b) and Figure 20 (a–f).

4 DISCUSSION

To build CNNs, the Python programming language [30] was used. Although any programming language theoretically can implement any ML algorithm(s). To speed up the development process, programming libraries are used. TensorFlow (TF) [34] was used extensively to construct, train and use the NNs. TF is an open-source software library for high-performance numerical computing, initially developed by the Google Brain team, and therefore has strong support for ML and DL.

The application of style transfer can be successfully integrated and embodied within the HDT-LFDS in multiple ways and different scenarios. Potential visual design and engineering stimuli are ubiquitous, if one is attentive enough to be able to capture and harness them to serve as sources of inspiration in the DEP [9].

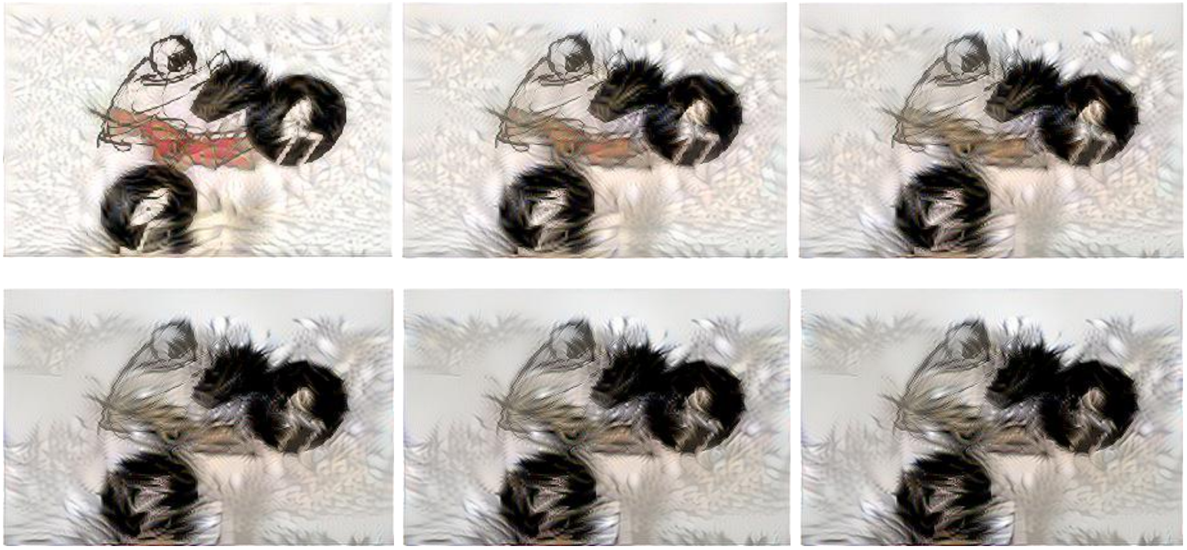

Figure 20: Image transformation through style-extraction in progressions, top left (a) to (f) bottom right (iterative sequential step-examples only).

For the use-case of these experiments, having such a delay in seeing one's results is just not practical, neither would the preparation of style representations in advance be. Therefore, a faster alternative need to be explored: by allowing the network (cloud) to give output as it trains, the user can already start to see what the network will be aiming for given more time.

In addition, it should be noted that this training-phase needs to be done for each new style-representation that is introduced to the system. To provide the image used for as style-representation on the spot: it does not need to be trained within the model a priori. However, once the training has been done, the model can be stored for later use, or even distributed to other systems. In doing so, a collection of trained representations can be maintained to mitigate for this drawback.

Furthermore, it allows you to directly tap into the computational capabilities of a Graphics Processing Unit (GPU), given that it is an NVIDIA GPU with so-called CUDA support [28]. The main benefit here is that the numerical computations that need to be performed can be calculated way faster on a GPU then a conventional Central Processing Unit (CPU). Another significant benefit of using a library like TF is that it allows you to efficiently distribute your ML-models post training.

This saves the effort to train a NN on every machine you aim to use your models on, since the time to teach a single network takes a lot of processing power, time and data.

TF is supported in multiple programming languages: besides the support for the Python programming language (which is the standard for these libraries) it recently also added support for the JavaScript (JS) [15] programming language (TF-JS). Unlike Python, JS can be interpreted by internet browsers. Therefore, software utilizing build ML-models and even trained in TF can be used in web-browser environments. Given that HDTs and HDTEs work in a browser and connected to internet it can access pre-trained ML-models and leverage their capabilities and requirements without the need of training their own network. Further testing and experimentation with HDT(E)s-CNN and CAI is part of on-going research.

5 CONCLUSION

For problem solving and synthesis, the use of an information-processing system (i.e., thinking-machines, design-machines, teaching-machines) that creates problem representations and possible solve-for-solution searches selectively through rhizomes of intermediate situations, seeking the goal (target) situation and using heuristics to guide its search could be a promising path.

At present, we work on two suggestions (options) how these algorithms could be implemented and integrated directly in the software of the HDTs and HDTEs. The first option would be to make the algorithm apply a layer-wise-adoption. The other option is to give the algorithm the capabilities to detect textures or different surfaces in an image. Then, the algorithm could apply specific modifications to each identified texture/surface.

The current status of the HDT-CAI system is the flexibility, the desired speed of the CNN is still a challenge. It must have undergone extensive training before being use functionally fluid and assistive in (near) real-time. Using a decent GPU, it takes the original algorithm roughly a few hours of training time before its usable.

Computation is a core resource in any machine learning (ML) project: its availability and cost, as well as the associated energy consumption, are key factors in both choosing ‘re-‘search directions and practical real-world adoption.

The most valuable next step for improving the algorithm two possible solutions arise. First option would be to make the algorithm apply a layer-wise-adoption. In between frames, the HDTs can check what has changed in-between captures, and only affect a particular style of alteration to these ‘new’ pixels. The other would be to give the algorithm the capabilities to detect textures or different surfaces in an image (see initial trials in Figure 19 and Figure 20). Then, the algorithm could apply specific modifications to each identified texture/surface. However, there are plenty of other areas for improvement.

Further research and experimentation are underway to explore and investigate other possibilities of CNN in HDTs and HDTEs. Creativity imbued with CAI is an ability to discover new ideas, define problems, discover blind spots and address challenges to solve for solutions. The paths open to curiosity are many or even too many, they are never straight or predictable, and it takes different and unpredictable amounts of time to traverse them [26].

‘Thinking Machines’ with GANs could assist in the creation and invention of new ideas or support the creative process, however, one needs to keep in mind that it combines only what it already knows but in novel ways. By tweaking the network, we could for instance allow the network to give output as it trains, early visualization makes it possible to either stop or influence the process or modify the style-transferring process. Optimization of the generator and discriminator networks sequentially is necessary constantly.

Curious minds, abhor ambiguities, feelings of ambivalence, and the lack of resolution. But curious minds discover uninhabited terrains of knowledge by questioning dogma and pondering the impossible. We remain "insatiable in intellectual curiosity, interested in big things, and happy in small ways," we will remain alive [46]. Curiosity exacts a cost, but the returns are great.

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