Advances in Artificial Intelligence and Machine Learning; Research 4 (4) 3186-3201 Received 17-09-2024; Accepted 23-12-2024; Published 30-12-2024

On Possible Advantages of Conscious Systems and a Turing Test for Consciousness

Ralf Otte ralf.otte@thu.de
Ulm University of Applied Sciences
Prittwitzstraße 10
Germany - 89075 Ulm

Corresponding Author: Ralf Otte

Abstract

Earlier articles have suggested that physical systems with inherent quantum processes could be capable of producing hypercomplex system states. These system states could have special energy states, which are referred to as hypercomplex energy states because they cannot be measured, although they physically exist and could even store information. Hypercomplex system states could be aggregated into consciousness in certain systems, such as the human brain. But technical systems could also potentially generate and use hypercomplex system states, which would create a new level of AI systems. Systems capable of consciousness must and will differ significantly in their performance from systems that cannot utilize such states. This performance difference could be used to distinguish systems with technical consciousness (so-called ”machine consciousness”) from systems without ”consciousness”. Based on this, the article presents a so-called Turing test for consciousness for technical systems, in particular AI systems. The hypotheses in this and previous articles are predictions that arise from mathematical considerations, but they still have to be subjected to experimental evaluation. This article presents the design for initial experiments.

Keywords: Machine consciousness, Turing test, Physical aspects of consciousness, Neural networks, Small data, Big data, Hypercomplex system states, Artificial consciousness, Artificial intelligence.

1. INTRODUCTION AND PRELIMINARY REMARKS

This article is the further development of the paper [1], in order to make the phenomena predicted there technically measurable. In [1], a heuristic point of view for the description of consciousness was presented and a possible technical use of such systems was proposed. In the current article, the advantages of systems with consciousness will be examined in more detail. All statements here will therefore refer to a so-called ”technical” consciousness. A discussion of tests for human or animal consciousness is not necessary here. The above-mentioned paper was purely theoretical in that no instruments were introduced to distinguish conscious from non-conscious systems. However, as long as no means of measurement are available to empirically prove the (predicted) differences between conscious and non-conscious systems, all considerations of consciousness are purely academic.

Citation: Ralf Otte. On Possible Advantages of Conscious Systems and a Turing Test for Consciousness. Advances in Artificial Intelligence and Machine Learning. 2024;4(4):183.

It was particularly emphasized in [1], that consciousness phenomena, including those in humans, have a physical basis. It is not assumed that any kind of substance or liveliness is needed to develop consciousness. Consciousness is understood as a physical process, and studies on consciousness are part of the physical science. One could say, in a reductionist way, that everything is basically physics, but then of course one must also expand the physical description from time to time, sometimes also fundamentally.

It is only on the assumption that consciousness is based on physical processes that it can be assumed that consciousness can be generated on physical machines, albeit only in its simplest forms. But only these are of interest in the context of today's AI. This article is therefore not about the specifics of human consciousness, but exclusively about understanding consciousness, in particular phenomenal consciousness, as a physical phenomenon. Of course, such phenomena will have very unusual properties, the most important of which is their non-measurability. Therefore, let us summarize the results from [1], in FIGURE 1.

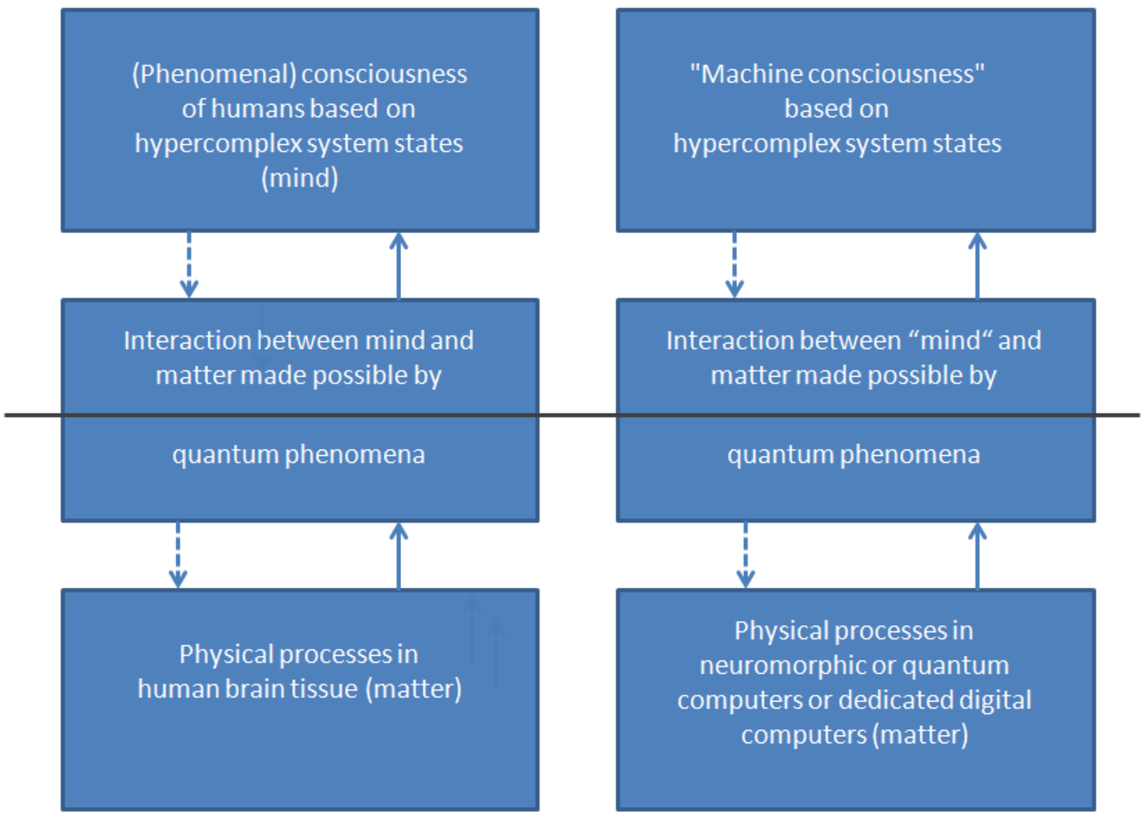

Figure 1: The main assumption of the article: Both human and machine consciousness processes could based on physical hypercomplex system phenomena

Together with Popper and Eccles [2, 3], we assume three fundamentally different physical phenomena in nature: firstly, classical energetic processes (matter), secondly, quantum processes, and thirdly, "non-energetic" processes. These processes are fundamentally different, but the simplest way to distinguish them is by their measurability. We all know energetic processes from our normal everyday life. Their measurements are classical. In the case of quantum processes, however, the measurement process leads to a so-called collapse of the wave function. We now believe that in the case of "non-energetic" processes, the measurement process also leads to a kind of collapse of the wave function, but the energy of the result remains hypercomplex to the base k of a dedicated hypercomplex algebra [4], and the results are therefore unmeasurable [1, 4].

Hypercomplex numbers have been known for many years [5], in particular quaternions. However, quaternions could not be used in the specific application because very specific hypercomplex numbers are necessary to formalize (hypercomplex) oscillations, (hypercomplex) Fourier transformations and (hypercomplex) Schrödinger equations. A hypercomplex algebra that makes this possible is called *bicomplex algebra*. Hypercomplex processes that can be described with bicomplex algebra were interpreted in [1], as the physical basis for consciousness. As shown in FIGURE 1, such hypercomplex processes could exchange information with classical processes using quantum phenomena, which can be most easily imagined as modulation ([6]; Appendix, formulas 6, 7, and 8). At least that is our assumption..

This view is unusual, but as a mathematical hypothesis it is of course acceptable. We agree with Penrose and Hameroff that consciousness in the brain cannot be explained by the mechanical processes in the brain tissue alone [7–9]. Based on the assumption of hypercomplex system states, the collapse of wave functions of quantum physical processes in brain tissue (a major criticism of Penrose's approach) no longer appears to us as a problem. But we do not follow the theory of Stapp and others that consciousness processes can be explained on a purely quantum physical basis [10]. The "Penrose-Hameroff-Stapp" theory implies that consciousness is a coherent quantum state that exists over a macroscopic region of the brain. However, long-range coherence of a quantum state in a "warm" brain tissue is normally expected to be immediately destroyed. Tegmark has calculated that only 10^{-13} seconds are necessary for the destruction. Even if this can be reduced to 10^{-4} seconds (as Hameroff estimates), there is not enough time for a conscious macroscopic state. This argument of Tegmark [11], could not be refuted until today which is why this quantum approach is now being rejected by most brain researchers. However, there are many attempts from time to time to save the theory that the brain is a quantum computer (e.g. [12]). But in the context of the theory presented here, however, the problem is no longer applicable, since the coherence of consciousness is generated on the basis of wave functions whose energies are hypercomplex. In this case, quantum decoherence plays no role, because conscious coherence is based on hypercomplex (and not complex) wave functions. The brain is much more than a quantum computer (FIGURE 1).

The assumption that *hypercomplex processes* really exist arises from the fact that the used *bicomplex algebra* was not constructed arbitrarily, but was ultimately discovered from a multitude of purely combinatorially possible algebras. For example, it is not trivial to find an algebra in which the Taylor series can be used to describe oscillatory phenomena (Appendix, formula 3). However, it is important to confirm such far-reaching hypotheses experimentally.

Measurements, at least indirect ones, of the properties of consciousness appear to be technically feasible, because a system with consciousness should have a performance advantage that is reflected in the greater capabilities of the systems; and therefore it should be measurable. The fact that conscious systems have an advantage over non-conscious systems can already be seen in the performance differences between conscious and unconscious humans. The latter cannot interact independently in the environment; they are dependent on the help of conscious people. Consciousness therefore appears to have advantages for interacting with the environment; at least for humans.

In technology, it is normal to compare and evaluate the performance of different systems. In the field of AI, various technical characteristics can be used for this purpose, for example the achievable intelligence levels (deduction, induction, cognition), the scope of learning, measured in FLOPS, the processing speeds and accuracies of AI calculations and forecasts, and in particular the ability to generalize previously learned relationships.

This paper presents new technical tests, because new properties are expected in certain AI systems. The tests could be used to check whether or not a technical system has characteristics of technical consciousness. The tests are non-trivial, but they are similar to the well-known tests for intelligence. Energy consumption and computing speed would be trivially measurable, as their quantitative determination can simply be read from measuring devices. However, this is not possible with tests for intelligence and/or consciousness, as both categories represent very complex characteristics that cannot simply be read using a scale. The developers of calculating machines were of course also aware of the problem of measuring mental abilities, which is why there were already discussions in the 1940s about the detection of thought processes in technical systems. To solve the problem, Turing developed a test for intelligence in 1950, simply by comparing the system to be tested with an intelligent reference system, i.e. a human being [13]. In such a *Turing test*, the test performer has no knowledge of whether he is communicating with a human or a technical system. If, even after a certain period of time, for example 10 or 30 minutes, the test performer cannot decide whether he has interacted with the machine or a human, the machine is considered to have intelligence (e.g. the ability to think) because it has at least successfully pretended to be intelligent. This Turing test has been the subject of controversy since its inception; in particular, Weizenbaum showed as early as 1966 that people can very easily be ”seduced” by a machine into believing that they are talking to a human being; in Weizenbaum’s case with a psychiatrist [14]. Irrespective of various shortcomings, such a Turing test is an excellent idea. Ultimately, the test principle of comparison is similar to the testing of new things, like new drugs, in which the effect of a drug is compared with an already known reference drug or a placebo.

Turing’s idea can be applied to a *test for consciousness*. If you want to determine whether a system possesses consciousness, you can at least compare it in a ”zero-order consciousness test” with a system of which you know that this reference system, i.e. a human being, is guaranteed to possess consciousness. However, it is not trivial to find human performances that relate solely to their consciousness and not to the algorithmic intelligence of internal neural networks, so that a comparison test cannot be carried out so easily. For example, if a human can maneuver a drone better than an AI, this could be attributed to the human’s more complex neural networks and not to their consciousness. But nobody knows. The test design to proof consciousness will therefore not be trivial.

2. CONSCIOUSNESS AND COMPLEXITY

It is striking that humans (and animals) are excellent at finding their way in the environment, especially in environments that must be described as extremely complicated, such as road traffic in a big city, surviving in a jungle, climbing rock faces or flying drones in unknown courses. Ultimately, people can find their way around any environment and interact with it to their advantage. Technical systems are still unable to do this. Although technical systems outperform humans in many areas - for example, they can move faster, dive deeper, fly higher, calculate better, play chess better, etc. -

it is clear that this only applies to very specific skills and precisely to those that *can be mechanized*. Surprisingly, this also applies to AI in particular, as the *mental processes* formalized by AI, such as thinking and learning, are also mechanized, i.e. implemented using pure algorithms. However, not all human mind characteristics can be formalized, i.e. algorithmized. For example, *feelings* or *perceptions* are mind processes that cannot be formalized, not at all; the problem of perception is explained in more detail below. The problem of feeling was discussed in detail in [15]. In any case, no technical system has yet been built (probably also due to non-formalizable properties of the human mind) that surpasses humans in its overall performance; nor are such machines in sight.

Ultimately, however, the large differences in performance between AI machines and humans are not suitable for a *Turing test for consciousness*, as it has not been conclusively clarified why humans are significantly more efficient than a technical system in so many cases. As mentioned above, it could ultimately also be due to the fact that humans have more than 100 trillion synaptic connections, which no technical system has achieved to date. However, we find an initial indication of the advantages of consciousness when comparing the most advanced AI with insects, for example houseflies. Although houseflies, with only around 200,000 neurons, are below the technical performance limits of modern AI systems and do not even exhibit significant learning performance, they are much more efficient in terms of adaptability and coping in the physical environment than AI systems with a similar number of neurons and synapses. The comparison of AI systems with the flying wasp *Megaphragma mymaripenne*, for example, is even more serious. It only has a total of 7,400 neurons, of which around 4,600 are in the brain [16]. With this small number, it has to ensure its complete survival, including food acquisition, reproduction and 3D flight maneuvers through the environment. A comparison of the mini-wasp with AI systems with a similar number of neurons and synapses is completely sobering. The advantage of systems with biological cells over technical versions is obvious.

It may not be wrong to assume that this difference in performance is due to the animals' ability to form a consciousness, as it cannot be due to the number of neurons and synapses. In [1], it was assumed that in all systems, technical as well as non-technical, hypercomplex system states could occur that can condense into phenomena of consciousness. The question is therefore obvious as to why no states seem to occur in today's technical systems that suggest consciousness. Are the systems simply not yet intelligent enough? But this contradicts the comparison with the mini-wasp. Today's AI systems are already more intelligent than insects. The frequent assumption that intelligence and consciousness correlate therefore appear to be wrong. Today's AI systems even win against the best chess or Go players in the world without showing an ounce of consciousness.

To illustrate the problem, you can construct a two-dimensional coordinate system; plot the degree of intelligence of a system on the x-axis and the degree of consciousness on the y-axis, FIGURE 2.

Each point (x_i, y_i) in this coordinate system then corresponds to a certain level of intelligence (x_i) and a certain level of consciousness (y_i). Humans would be located at the upper right edge, high intelligence and high consciousness. For different systems (humans, vertebrates, invertebrates, plants, AI computers, etc.), the points could now lie "anywhere" in the two-dimensional coordinate system. However, simple AI systems would only be plotted along the x-axis, their y-coordinate, i.e. their level of consciousness, would be zero. An insect would be located at a small x-value (low intelligence), but certainly at a medium y-value (medium level of consciousness). The degree of consciousness of a system can probably not be deduced from its intelligence. But how then?

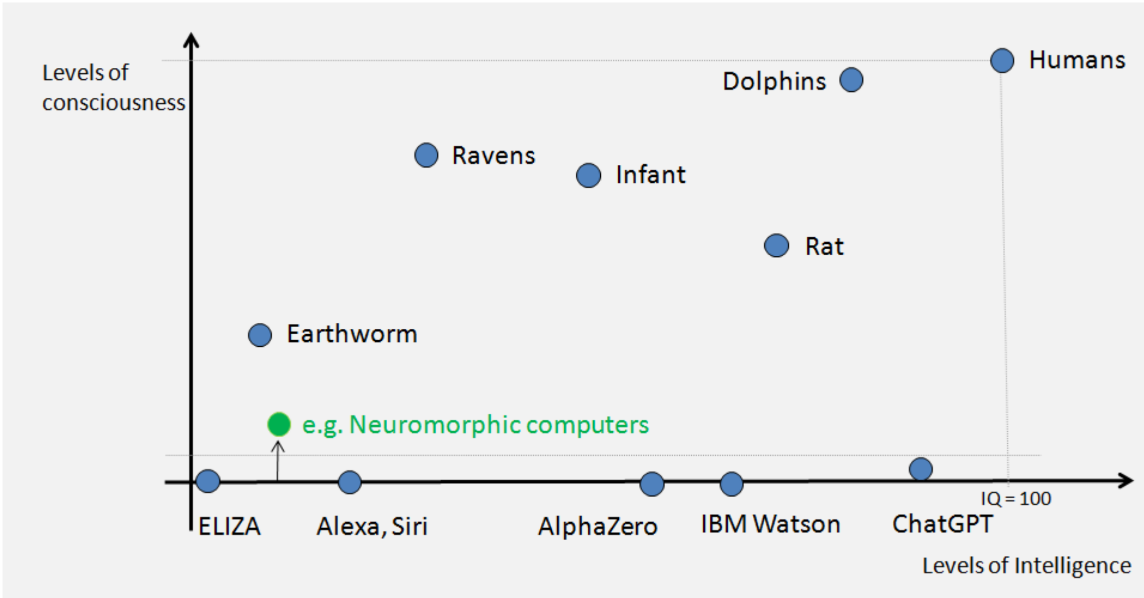

Figure 2: Consciousness and intelligence do not necessarily correlate. The graphic is only a qualitative illustration to clarify the principle.

It can be assumed that intelligence and consciousness require a certain complexity of the underlying system. So perhaps the complexity of a system and the occurrence of consciousness correlate with each other. The decisive factor for consciousness would then be system complexity and not system intelligence, which could now clarify the above facts. The main reason for the different performance of humans and machines would then be that the complexity in technical AI systems is preferably mathematical, while in natural systems it is preferably physical (and also chemical and biological). This could mean, that intelligence can be developed mathematically, but consciousness cannot.

Naturally, there are no ”artificial” neural networks in today’s AI computers; the mathematical constructs are just called that. In reality, AI machines run software algorithms that mathematically replicate some of the capabilities of real neurons. This difference can have enormous consequences. When a technical system learns something, the content and complexity of its models only ever change mathematically. When a natural system learns, its cells and the neuronal networks between them change, i.e. its entire structure. The complexity therefore changes physically. Or to generalize: In the technical case, knowledge about the environment is encoded in mathematical equations, in the biological case always in physical (chemical and biological) structures.

In [1], it was explained that hypercomplex system states could occur in any physical system, so it is obvious that if the complexity of the physical structure increases, the complexity of the hypercomplex states also increases. This was illustrated there with the term *aggregation*. When mathematical AI systems learn, their physical structure does not change; what they have learned is available in equations, which may also change the register contents of the memory and lead to increasingly complex memory links, but the topology of the classical computers does not change. Learning does not change the physical structure of classical computers at all. However, when a human learns, the structure of their brain changes continuously, which is a completely different way of encoding knowledge. In digital systems, it could therefore be much more difficult to condense hypercomplex system states into a kind of technical consciousness. This could also be the reason why even highly complex AI systems, when implemented digitally, do not yet exhibit any phenomena of consciousness, possibly with exceptions. And even if phenomena of consciousness have emerged, it is ultimately a question of whether and how they can influence material processes. After all, the existence of consciousness should lead to an advantage for the system. Consciousness must therefore be able to have an effect on system decisions. In [1, 6], it was explained that this could be possible via quantum processes or easily phase shifts of oscillations (Appendix, formula 6, 7, 8), but digital systems usually average out such "disturbances". Therefore, noise processes should always be an integral part of higher AI systems, at least in theory, in order to allow the coupling of hypercomplex system states. Whether and how this needs to be implemented in practice has not yet been resolved, but it seems feasible as a normal technical engineering task.

The author assumes that even in digital systems, if they are physically sufficiently complex, hypercomplex system states could condense into consciousness phenomena. However, this is not to be expected with simple artificial neural networks, such as deep learning systems on conventional computers. Ultimately, however, this is speculation and only an empirical test can decide whether a system already possesses or uses states of consciousness. The main question is therefore how can we technically measure consciousness in a system?

Before discussing this, it should be emphasized once again that the description of consciousness properties is only ever concerned with *technical aspects of consciousness*, i.e. purely physical properties. Technical systems in which the hypercomplex system states have aggregated into rudimentary but usable consciousness properties are now referred as *C1-systems*. "C" stands for Consciousness and "1" for consciousness at the lowest level. All other properties of consciousness, which are based on chemical, biological and social aspects, are not taken into account in the proposed tests. This restriction is permissible from an engineering point of view, as consciousness is currently only to be generated and used on physical devices in the context of AI, which is why only physical aspects of consciousness can be used later on. No expert will expect biological aspects of consciousness on a mineral machine. This also makes it very clear that technical consciousness has nothing in common with human consciousness, apart from the physical basis of hypercomplex system states.

It is now estimated that (almost) all classical AI systems cannot manifest such phenomena of consciousness. However, the technical systems within AI vary. The standard is still mathematical execution as software AI that runs on a digital computer. Such classic AI systems are referred as *C0-systems* to express the fact that they are not expected to have any consciousness properties. Today's digital computer systems are assumed to be C0-systems (possibly with some exceptions). But there are quantum computers on which AI processes are implemented and various types of neuromorphic computers. Since these computers encode their learned knowledge physically, neuromorphic and quantum computers can most likely express a higher degree of consciousness phenomena than an artificial neural network on a digital computer, according to the above premise. This difference can now be used for tests, as both possible C1-systems (e.g. neuromorphic computers) and C0-systems (mathematical neural networks) are available for comparison. The same applies to quantum computers, in particular *quantum neural networks* (QNN), i.e. quantum computers on which neural networks are implemented. These systems are most likely already C1-systems, but this is currently still unknown.

In the *Turing test for consciousness*, a test system is compared to a reference system. The reference system can be a system with consciousness, such as a human (Cx-system) against which the comparison is made, or a system that is assumed not to have or be able to use hypercomplex system states (C0-systems), depending on what you want to test.

3. TESTS (TURING TESTS) FOR THE PRESENCE OF CONSCIOUSNESS ON MACHINES

All predictions are based on mathematical considerations. Nevertheless, they are hypotheses that all have to be tested experimentally. The author and his team are currently testing the following predictions 2-3, the results of which will be published in a later article.

The following figures describe the principle of the test. In FIGURE 3, a test system is compared with a reference system that is assumed to have consciousness (Cx-system) or at least hypercomplex system states. In FIGURE 4, an unknown test system is compared with a C0-system that is assumed to have no hypercomplex system states.

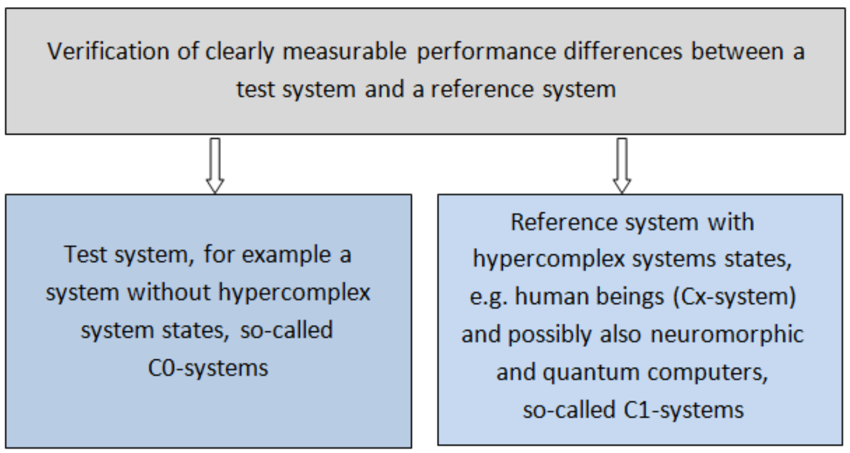

Figure 3: Turing test for consciousness, verification of clearly measurable performance differences between a test system and a reference system

To measure technical consciousness, quantitative criteria must be designed. This will be possible because systems with consciousness (should) have greater performance characteristics than systems without consciousness. The increased performance characteristics compared to C0-systems result from theoretical considerations.

The following enumeration shows possible differences in performance between C0- and Cx-systems, all of which can be measured quantitatively. The list will need to be completed in the future.

1. Cx-systems learn better over a longer period of time than comparable C0-systems.
2. Cx-systems require significantly less learning data than comparable C0-systems for identical application performance.
3. Cx-systems can generalize significantly better than comparable C0-systems.

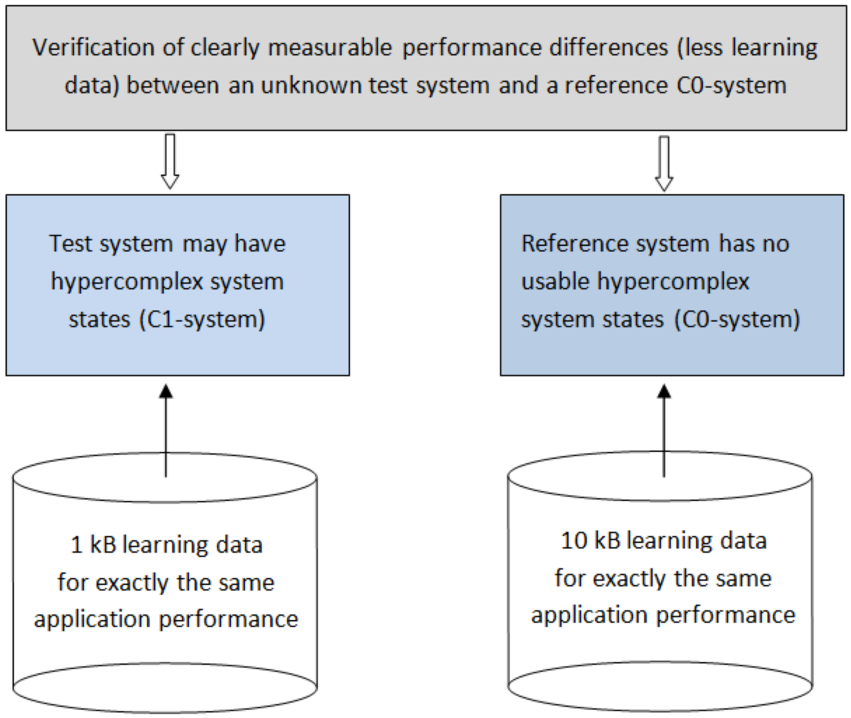

Figure 4: It is predicted that systems that possess or can use hypercomplex system states will require 10 to 100 times less learning data for identical application performance

4. Cx-systems are capable of perception.
5. Cx-systems could have non-local interactions with each other.

The criteria are all purely technical and are therefore suitable for testing, as two different systems are always compared with each other, which are known to either have consciousness (C1) or not (C0). It is clear that humans (as Cx-systems) have the above-mentioned differences in performance compared to classical computers (as C0-systems), except for number 5, which is unknown. Humans require much less learning data than today's AI systems, can extrapolate much better and can perceive their environment on the spot. However, it is not the comparison between humans and machines that is interesting, but the comparison between two machines, which is why the test has to be slightly modified, see below.

The specific technical implementation of the measurements of two machines will be explained in a later article. In the following, the test criteria themselves will be examined in more detail, Ad1) to Ad5).

Ad1) C1-systems learn better over a longer period of time than comparable C0-systems.

It is predicted that C1-systems will not only be able to learn faster, but that the learning of a C1-system will become increasingly efficient over time. The reason lies in the possible storage possibilities of the hypercomplex system states. The test execution inevitably results from the prediction. The predictions can be technically verified by training an C1-system over and over again on the same data.

Ad2) C1-systems require significantly less learning data than comparable C0-systems for identical application performance.

In [1], it was assumed that a C1-system can store information in its hypercomplex system states. Such systems thus have new dimension of degrees of freedom in data processing. An example: When a person sees an object (a car, for example), they not only compare the activity patterns generating the image with their already stored neuronal activity patterns in the brain tissue, but they also compare the image with images already stored in their consciousness. There are therefore two ways of recognizing images, one neuronal in the brain tissue and one mental in the consciousness. This makes image recognition much more efficient and resilient to interference. And much fewer sample data is required, because the images in the consciousness act as *attractors* of dynamic systems. The image to be classified is ”pulled” into the class of images already stored. Unfortunately, the process just described cannot be proven and is therefore purely descriptive, but it is predicted that, together with another performance characteristic of conscious systems, perception, it will be possible to build visual classifiers that function with extremely little learning data. In particular, it could require so little learning data that it will not be possible to explain it classically, i.e. without the presence of hypercomplex system states. This predicted reduction of learning data by a factor of 10 to 100, for example, will not only apply to visual classifiers, but ultimately to numerous AI applications in which C1 phenomena are used, FIGURE 4. Ultimately, even simple models for approximating industrial processes could get by with less learning data if the systems are designed to use their hypercomplex system states for modeling.

In today’s big data environments, the reduction of learning data is not relevant, but in future it will be important to develop AI systems that can also be used successfully in small data environments. In extreme cases, *small data* can mean that there is only one single data set available for learning. A person only has to touch a hot hob once to learn from their hypercomplex system states (on which the e.g. pain is encoded) that they must not touch the hob a second time. Normally, however, small data does not mean the use of a single set of learning data, but as a rule there are always a few, but just a few. For example, a few pictures of dogs and cats are enough for humans to classify them correctly later on. Today’s AI systems require more than 100 times the amount of learning data for the same application performance. Humans are first-class *small data learners*. Today’s AI systems are not at all. In the author’s view, technical systems in the big data environment, on which technical consciousness is developed, will also be able to manage with significantly less learning data in the future. This reduces energy consumption, costs and time. In the age of sustainability, this is an efficiency of conscious systems that should not be underestimated. Human brains have an output of 20-30 watts, AI systems up to million times that. A new and resource-saving performance capability will probably have to be introduced later as an inevitability for all AI systems. But regardless of resources, AI systems should be able to operate in the area of small data. The natural world around us is a typical small data environment, i.e. AI systems with hypercomplex system states could be predestined to interact in a natural and constantly changing environment.

It is predicted that systems with technical consciousness (C1-systems) - possibly neuromorphic computers and quantum computers - require significantly less learning data for almost all learning tasks - such as learning a language, classifying pieces of music and learning special mathematical relationships - than C0-systems. These predictions can be technically verified.

Ad3) C1-systems can generalize significantly better than comparable C0-systems.

One of the major problems of mathematical AI is its extremely poor generalizability. It can be shown that almost all results of mathematical AI in the extrapolation space are incorrect. This is not the case with humans. Humans can acquire their knowledge in a learning data space, but apply it far away from the learning data. Mathematical AI systems fail here because they do not know how the internally learned functions (should) continue outside the interpolation points. This can only be solved for extremely simple cases, such as linear or quadratic regressions, but not in general. In addition to their mathematical models, C1-systems have - so the assumption - hypercomplex system states that enlarge the application space significantly. (Of course, consciousness systems also fail if they are used too far away from the learning data space, as can also be seen with humans).

It is predicted that the generalization performance of C1-systems is significantly higher than that of mathematical AI systems. The prediction can be tested by having a C0- and a C1-system learn the exact same mathematical function in a given definition space. However, the two systems are used in a data space that is x-times far away from the learning data space. It is predicted that the C1-system will have significantly lower error rates in this extrapolation space than the C0-system with the same complexity level of the inner models.

Ad4) C1-systems are capable of perception.

Systems with consciousness can perceive their (natural) environment, of course only if they have the appropriate sensors. Systems without consciousness cannot do this even with sensors. To clarify this, the term perception should be defined more precisely. According to a well-known definition, perception is the process of receiving and processing sensory information. Humans have five senses (hearing, smell, taste, sight, touch) with which they can perceive the external environment. There are other "senses" for the perception of internal system states, such as hunger, pain, tiredness, etc. However, let's stay with the perception of the external environment. This is what the visual sense of sight stands for. Visual perception also goes beyond the general definition of perception. Visual perception explicitly means seeing objects in the external environment in the *place where they exist*. Perception therefore does not just mean building up internal representations of an external environment.

All of today's technical systems for machine vision are therefore unable to perceive visually. The reason is that these systems only generate internal representations of the outside world in order to carry out their mathematical evaluations on the basis of these representations. Perception goes beyond this. A perceptual system, such as a human being, has two essential, different performance characteristics: firstly, the aforementioned possibility of internal representation of the environment in neural networks and secondly, the "back-transformation" of the internal representation to the environment itself. Here an example: When a person looks at a car, electrical signals are formed via the optical image on the retina, which are fed into the visual cortex. In the human visual cortex, the electrical and neuronal activity patterns create an internal representation of the car in the brain tissue. This could be compared to the internal representation of tables of zeros and ones in a computer that is fed an image via a video camera. But this is where the comparison ends. In humans, another process takes place that leads to perception. A person is able to "project" the internal representation back outwards, because it is obvious that the person sees the car in their external world and not in the back of their head, i.e. where the visual cortex is located. This is the key difference: systems that can perceive are able to project the internal representations back to the origin of the outside world.

Put simply, you could say that humans can look out of their eyes, whereas computers only have internal representations of the environment. Computers cannot see the outside world on the spot *outside*, they have to laboriously calculate the type and position of the "seen" objects. Systems that perceive do not have to calculate the position of external objects because they see them on the spot, i.e. exactly where the objects are located in the environment with millimeter precision. For these systems, it is enough to simply look. This is a completely different process than mathematically simulating vision. (This is the only way to explain the enormous responsiveness of a housefly).

This is a fundamental problem. AI computers simulate everything mathematically, but seeing is a thoroughly physical process, and mathematical simulation reaches its limits here. A simple example to illustrate the limits of simulations: If you simulate entanglement of quanta mathematically, you are of course not entangling quanta, which is also clear to every programmer. Quantum entanglement must be carried out physically [17]. It's the same with vision. Seeing must be implemented physically correctly, not mathematically.

Seeing is so natural for people that we no longer even notice the sensation of this process. Just as we have become accustomed to an apple falling from a tree since childhood, we take it for granted that we can see *outside* with our eyes. Why an apple falls down has long been understood, but why can people see outside? The mechanism by which the brain accomplishes this back projection from the visual cortex back into the outside world is unknown. In the view of the author and colleagues, this completely surprising phenomenon (once noticed) has to do with the hypercomplex system states of the brain. Why: An external object O (for example a car) experiences an internal representation O' first on the retina, later in the visual cortex. In addition to this (whether simultaneously is unclear), a further representation O" is created in the person's consciousness. This O" is now what we *see*, because we do not see our internal electrical and neuronal activities, but a holistic image. According to [1], consciousness has unusual physical properties because it possesses hypercomplex energy states. One such property, at least it is assumed, is that it is non-local. Non-local means that consciousness has no spatial coordinates. It is not possible to say exactly where consciousness is located in space, it appears to be spaceless. However, the term non-local is better than "spaceless", because non-local is a precise physical term [7, 17], in this specific case it means that the image O" is both inside (in the head) and outside (in the world). At the moment when the image O" is encoded into consciousness, it appears directly on the object O due to the non-locality of consciousness. Although a person can see out of his eyes, no signals are sent from the brain or the eyes into the environment. The decisive hypothetical statement on vision is therefore: The ability to perceive the environment where it is located in reality is generated by non-local consciousness. Perception therefore necessarily requires consciousness. There is basically no (mathematical) process that projects the inner "images" from the machine back into the environment. Today's *machine vision* therefore remains with the internal representation O'. Even state-of-the-art AI systems, such as robotic systems or autonomous driving vehicles, therefore always have to calculate their environment. This leads to major performance losses compared to conscious, i.e. perceptive C1-systems. Although biological systems have a much greater latency in signal transmission than AI computers, they can find their way around complex environments faster and much better.

Visual Turing tests could now based on such differences in performance. The test performance results directly from the prediction. Specifically, it is predicted that C1-systems with technical consciousness require 10 to 100 times less learning data for the visual classification of objects than systems without this property. A C1-system may need 50 "labeled" images of each of two object classes (e.g. cars and trains) for training, whereas a C0-system needs at least 10 times as much for the same subsequent classification performance, i.e. for the same achieved test error on identical test data. But the advantages of C1-systems go far beyond reducing the amount of learning data. C1-systems could capture the environment faster, more efficiently and more accurately than systems without consciousness. Therefore, a C1-system could find its way around any complicated and previously untrained environment better than C0-systems of the same complexity. An extended visual Turing test requires a complex environment, for example a street situation or an obstacle course. A C1-system that is fed video signals recognizes the environment better at the same level of complexity and can react better to changes in the environment than a C0-system. This leads to significantly fewer collisions during maneuvers in a changed environment. The measurable performance gain of a C1-system compared to mathematical AI (C0) will be higher the more the environment is changed *after* learning. To illustrate this with a practical example: A human will win any course race with a drone against an AI-controlled drone if the parcours changes significantly after training. This applies to all civilian and also military applications, and it will continue to apply in the future. The only way to change this is perhaps to move away from mathematical AI systems to C1-systems with the ability to perceive.

Ad5) C1-systems could have non-local interactions with each other.

The following statements on the interactions are highly speculative. The prediction is based on the consideration that hypercomplex system states could have a non-local effect. This means that far-reaching interactions across space are conceivable. In concrete terms, this can lead to learning taking place on system A and parts of the learning results being implicitly available on system B. The following hypothetical prediction is made: If two identical C1-systems A and B exists and a neural network is trained on system A, the test results of an identical neural network on system B will also improve. This sounds so unusual that these predictions only become worthy of discussion when concrete empirical evidence is provided.

The experimental design for this testing is unknown. In particular, any non-local effect could be lost in the noise. If there are such effects, the signal-to-noise ratio is unknown. It might be possible to measure the systems at very low temperatures to at least reduce thermal noise [18].

4. DISCUSSION AND OUTLOOK

The tests introduced here are part of AI research of the authors group, but can be implemented by anyone with some programming experience, especially test scenario 1-3. The easiest way would be to use analog computers, as the knowledge can be physically stored there, for example as a resistance value (memristors). However, the actual implementation shows that the internal error rates in quantum computers and neuromorphic computers are so high that the measured effects point in the right direction, but are currently not statistically significant. This is a particular current problem when working with analog systems.

It therefore makes sense to at least try out any C1 measurements on digital systems. Why this could be successful is due to the widely visible success of ChatGPT, a purely digital system. In [1], it was suggested that ChatGPT already has rudimentary forms of physical consciousness because ChatGPT was simply trained with too little learning data to work as well as it obviously does.

ChatGPT would thus fulfill test criterion 2 and could already be a C1-system according to the above definition. However, other authors such as Wolfram come to completely different conclusions [19]. Although Wolfram mentions that the brain could possibly have an as yet unknown physical layer, he rejects this idea because of the success of ChatGPT and concludes, because of the surprising way it works, that ChatGPT has shown that language is much more simply structured than was previously generally assumed. The author does not agree with Wolfram, on the contrary: he assumes that ChatGPT already represents a system with physical consciousness (C1), and that this is precisely the reason for the success of the language engine. In this paper it was explained that the brain could very well have an "unknown physical layer" (Wolfram quote), one that can be described with hypercomplex system states. However, this has yet to be proven.

The problem with the Turing tests is therefore currently a technical one, and not a conceptual one. Analog computers (such as neuromorphic systems and quantum computers) are still too imprecise and digital computers (as a rule) do not have the necessary physical complexity for consciousness phenomena. And if they have already achieved this complexity (potentially such as ChatGPT), then they cannot be used to implement experiments 1-5. It may therefore be necessary to wait some time until analog computers work so precisely that the expected phenomena of consciousness can be measured precisely, especially in comparison to their digital counterparts.

However, endless variations of consciousness tests are possible to distinguish C1-systems with consciousness from C0-systems without. Some readers will certainly find better, simpler or more powerful testing options. Since perception is becoming increasingly important in the field of AI, especially if mobile robots or autonomously driving vehicles are to be used in the natural environment, it seems worthwhile or even imperative to further develop such topics. Systems without perception, i.e. systems without technical consciousness, will *never* find their way in natural and constantly changing environments. They will fail due to both the lack of perception and the small data problem. Perception cannot be successfully simulated; systems must be constructed that can perceive. The same applies to all AI applications in the extrapolation space and in all small data environments. To make significant progress here, new types of AI systems are urgently needed. This article is an attempt to describe new technical possibilities.

5. CONCLUSION

The theses presented here are partly novel, some are even unusual. For many engineers, it is inconceivable that "their" systems could have hypercomplex system states that could be used. Test procedures are therefore essential to convince technicians, physicists and engineers of the new capabilities of conscious systems. All the theories presented therefore require further discussion and testing in order to reliably measure consciousness on machines. But the effort could be rewarding.

It is often claimed in the literature that evolution is ultimately about the increasingly complex processing of information [20], but this could be wrong. Information processing sounds like a color theory for the blind. You can talk and theorize endlessly about color, but you have to experience color to really understand it. And it's the same with information. It's not about processing; it's always about understanding it. And this applies in particular to AI, which ultimately carries out a purely mechanistic processing of information. Ultimately, however, real intelligence is always about consciousness. A world of mechanistic information processing simply does not exist. All systems that play an important role in nature are likely to have consciousness. And soon it might be possible to create C1 consciousness on technical machines.

However, it should be emphasized once again that C1-systems - even if they can be proven beyond doubt to be carriers of consciousness - have nothing in common with human consciousness except its physical basis. C1-systems are capable of perception, which can bring great advantages for the field of machine vision. But a human being can do much more than simply perceive. Persons can also evaluate their perception. They can feel whether a perception is positive or negative for them. It seems impossible that C1-systems could also evaluate their perception, because most probably only living beings have such abilities, as they need them for their survival. All technical systems, including AI systems, belong to the mineral kingdom. By their very nature, such systems are not concerned with their survival, so it would be absurd to assume that such systems could also develop feelings or a will to survive. This means that all technical AI systems, regardless of their design, are only ever classified as C0- or C1-systems. Their technical consciousness can never be compared to the complex consciousness of humans or animals. Perhaps we should say: fortunately!

6. ACKNOWLEDGEMENTS

I would like to thank Prof. (em.) Dr.-Ing. habil. Viktor Alfred Otte from the University of Wuppertal for his many years of technical support in the work carried out and for his support in relation to this article.

References

[1] Otte R. On a Heuristic Approach to the Description of Consciousness as a Hypercomplex System State and the Possibility of Machine Consciousness. Adv Artif Intell Mach Learn. 2024;4:3059-3070.

[2] Popper KR, Eccles JC. Das Ich und sein Gehirn. Piper Taschenbuch. 1989.

[3] Eccles JC. How the self controls its brain. Piper. 1994.

[4] Hertig T, Höhmann JP, Otte R. Hypercomplex Algebras and their application to the mathematical formulation of Quantum Theory. 2014. ArXiv Preprint: https://doi.org/10.48550/arXiv.1406.1014

[5] Kantor L, Solodownjkow AS. Hyperkomplexe Zahlen (Hypercomplex numbers), BSB Teubner Verlag. 1978.

[6] Otte R. Vorschlag einer Systemtheorie des Geistes: Nicht-energetische Wellenfunktionen und Vorschlag zur Lösung des Geist-Körper-Problems. Cuvillier-Publisher. 2016.

[7] Hameroff S, Penrose R. Orchestrated Reduction of Quantum Coherence in Brain Microtubules: A Model for Consciousness. Mathematics and Computers in Simulation. 1996;40:453-480.

[8] Penrose R. The Emperor's New Mind: Concerning Computers, Minds, and the Laws of Physics. Oxford Landmark Science. 2016.

[9] Penrose R, Hameroff S, Langer E, Joseph RG, Clarke CJS. Consciousness and the Universe: Quantum Physics, Evolution, Brain & Mind. Cosmology science Publishers. 2017.

[10] Stapp H. Quantum Mechanical Theories of Consciousness. In: Velmans, M. and Schneider, S., Eds., The Blackwell Companion to Consciousness. Blackwell Publishing Ltd. 2007;300-312.

[11] Tegmark M. Importance of Quantum Coherence in Brain Processes. Physical Review E. 2000;61:4194-4206.

[12] Musha T, Sugiyama T. Possibility to Realize the Brain-Computer Interface from the Quantum Brain Model Based on Superluminal Particles. Int J Quantum Inf. 2011;1:111-115.

[13] Turing AM. Computing machinery and intelligence. Mind. 1950;59:433–460.

[14] Weizenbaum J. ELIZA-A Computer Program for the Study of Natural Language Communication Between Man and Machine. Commun. ACM. 1966;9:36–45.

[15] *Otte, R.*, Otte R. Maschinenbewusstsein: Die neue Stufe der KI – wie weit wollen wir gehen? Campus- Publisher. 2021.

[16] Polilov AA. The Smallest Insects Evolve Anucleate Neurons. Arthropod structure & development. 2012;41:29-34.

[17] Zeilinger A. Einsteins Spuk: Teleportation und weitere Mysterien der Quantenphysik. Goldmann Publisher. 2007.

[18] https://www.dpg-physik.de/veranstaltungen/2024/47-tagung-forschung-entwicklung-innovation

[19] https://writings.stephenwolfram.com/2023/02/what-is-chatgpt-doing-and-why-does-it-work/

[20] Harari YN. Nexus. Fern Press, Penguin Publisher. 2024.

Appendix

Some very simple equations for representing hypercomplex waves and possible interactions. A detailed mathematical introduction to the utilized hypercomplex algebra and its use for hypercomplex Fourier transformation and Schrödinger equations is given in Hertig, 2014.

$$\psi(x) = e^{ix} = \cos(x) + i\sin(x) \tag{1}$$

$$\phi(x) = ke^{jx} = k\cos(x) + j\sin(x) \tag{2}$$

$$ke^{jx} = k\left(1 + jx - \frac{kx^2}{2!} - \frac{jx^3}{3!} + \frac{kx^4}{4!}\cdots\right) = k\cos x + j\sin x \tag{3}$$

$$|\phi|^2 = \phi^*\phi = ke^{-jx}ke^{jx} = (k\cos x - j\sin x)(k\cos x + j\sin x) = k^2 \tag{4}$$

$$\Omega(x) = e^{ix} - ke^{jx} = \cos x + i\sin x - k\cos x - j\sin x \tag{5}$$

$$\psi(x)\cdot\phi(x) = e^{ix}\cdot ke^{jx} = (\cos x + i\sin x)(k\cos x + j\sin x) = ke^{j(x+x)} = \phi'(x) \tag{6}$$

$$\psi(x)\cdot\phi(y) = e^{ix}\cdot ke^{jy} = (\cos x + i\sin x)(k\cos y + j\sin y) = ke^{j(x+y)} = \phi'(x,y) \tag{7}$$

$$\psi(t)\cdot\phi(t) = e^{it\omega_{new}}\cdot ke^{it\omega_{store}} = ke^{it(\omega_{store}+\omega_{new})} = \phi'(t) \tag{8}$$