A Communication-based Model of Consciousness

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Abstract—If one had a full understanding of consciousness then it should be possible to create artificial consciousness. It is frequently argued that qualia are subjective and are impossible to re-create artificially. However, qualia are grounded in reality and therefore are not arbitrary. We show this for the quale color. The perceived color corresponds to a three-dimensional value that describes the spectral reflectance function of an object. Perceived color is comparable across individuals. Given this result for color, it is presumed that this also holds for other qualia like pain, hunger or love. According to the theory presented here, an assembly of neurons processes perceptions and is in charge of communicating this information to other members of the peer group. This assembly corresponds to conscious information processing. The job of this assembly is (a) to analyze what the body experiences (internal and external), (b) to keep a record of it, and (c) to explain these experiences to members of the peer group.

I. Introduction

The question of how consciousness is created is probably one of the most pressing research questions of all time. Every human being has a first hand knowledge of what consciousness is. It could (very briefly) be summarized as awareness of internal and external existence. We are still unable to fully understand what it takes to create consciousness. However, in recent years considerable progress has been achieved.

Color perception is of paramount importance to understanding of consciousness. Many philosophical arguments have been exchanged on this subject. In particular, it is of great interest to know whether my color perception of "red" is the same as your color perception of "red". We will argue here that this is indeed the case. Results from human visual processing and the area of color constancy support this view. The human brain estimates the reflectance function of an object and we argue that the quale color is due to the mathematical structure of the space of reflectance as represented inside our brains.

Another important question is whether consciousness has any causal power. With reference to Libet's experiments (Libet et al., 1983)) one could argue that consciousness has no causal power because the experience of *conscious will* occurs after a readiness potential has been measured. However, consciousness does not lack causal power. The main evolutionary use of consciousness is communication between peers. This communication can occur verbally or non-verbally (by signalling with the body or by writing on a piece of paper). Somewhere in the brain there must be an assembly of neurons in charge of storing action plans, i.e. a kind of "todo list" for the body. The neural assembly which is in charge of conscious perception presumably enters plans like uttering something or writing down a sentence into this "todo list".

If consciousness is assumed to insert plans into a planning section of the brain, a feedback loop is created because actions can also be perceived. This feedback loop is a second feedback loop akin to the feedback loop for normal unconscious behavior. Due to the additional processing, it is a slower loop. So there are two feedback loops. One loop is used for immediate behavior such as walking or catching a ball. The second feedback loop is much slower than the first. It is a result of an individual communicating with peers and also with him or herself. For both loops, behavior is (computationally) determined by the environment and the internal state of the individual. For many activities that require real time reactive behavior consciousness probably lacks immediate causal power because

the conscious feedback loop is executed much slower than the unconscious feed back loop. Lacking immediate causal power it is not meant to imply that consciousness has no causal power. The conscious feedback loop with its evolutionary purpose (communicating with peers) did not evolve to carry out immediate control of the organism. Immediate control of the organism is carried out by the unconscious control loop.

According to the theory presented here, an assembly of neurons in the brain is in charge of consciousness. The job of this assembly is (a) to measure/analyze what the body experiences (internal and external), (b) to keep a record of it, and (c) to explain these experiences to members of the peer group. We argue that all problems that one may have with what consciousness is or seems to be, will go away if one views it like this. This contribution will review evidence supporting this view from consciousness research. We explain how the brain estimates reflectance and then assigns labels, i.e. color names to these estimates. This in depth description of the quale color leads to implications for machine consciousness. We will see that there is great support for this view on consciousness.

II. EVOLUTIONARY ADVANTAGE

The primary objective of an organism is survival. In other words, the body (controlled by the brain) behaves in a way that is reasonable for the environment. Our body and mind is a product of evolution (Darwin, 1996; Maynard Smith, 1993; Dennett, 1995; Cairns-Smith, 1996; Pinker, 1997)). In order for an organism to reproduce, it of course needs to survive long enough to be able to reproduce its DNA. It is not necessary that every individual reproduces. However, if the average fitness of a species is below 1 for a sufficiently long time, i.e. less than one offspring is created per individual on average, it will become extinct. Consciousness, like many other traits confers an evolutionary advantage. Graziano et al. (2019)) also asserts that consciousness is socially useful. If consciousness had no evolutionary advantage, then it would never have arisen in the first place.

Interestingly, sometimes we are consciously addressing the task at hand while at other times, we seem to do things automatically, as if on auto-pilot (Hameroff, 2010)). While on auto-pilot, consciousness still exists but is addressing things that are not of immediate concern to the behavior of the individual (like solving complex mathematical problems). The mind can attend either to internal issues or to external issues. The internally directed attention is associated with the so called default mode network whereas externally directed attention is associated with the dorsal attention network (Benedek et al., 2016)). According to the view presented here, the auto-pilot mode is actually the normal mode of operation. In other words, consciousness is not required once the body has learned to carry out a certain task. Consciousness only takes notes of important occurrences. That's why it appears as if we consciously carry out a certain task while in reality we are only taking notes when something interesting (learning a new task) happens. So, control and perception, i.e. consciousness/communication,

are two separate issues. The separate processing of perception vs action is well established (Goodale and Milner, 1992)).

On top of this auto-pilot mode of operation we have, as an add-on, communication. We can communicate using various methods: language, sign language, drawings, written texts (Stangor et al., 2019; Cohn, 2012)). We could write a message on a piece of paper and hand it to somebody. We can also communicate non-verbally via body language. The communication center is equivalent to the homunculus (Dennett, 1991)). It "perceives" (or rather processes data from) external or internal events. It is observing what the organism is doing. It will be specified below what this "observing" exactly entails. According to this view, an organism without consciousness (and hence without any means of communicating), is perfectly fit to survive and reproduce. However, consciousness or rather the communication center provides an evolutionary advantage.

With consciousness, plans and experiences can be communicated to peers. Suppose one individual of a group of people is hungry. This individual separates from the group to get some fruit from a tree. Before he leaves the group, this individual can tell other persons who also belong to the group that he is hungry (conscious perception of empty stomach) and inform others that he will go to get some food. This has the benefit that the group will know what he is about to do. The peers will wait for his return. The plan to go and get something to eat has been formed by the unconscious brain (probably because his stomach is empty and there is no food located nearby). The person might say "I am hungry. I will go and eat a banana". The information "hungry" has been gathered via processing the internal state of the body. "I will go and eat a banana" is a statement about what the body is about to do next, i.e. the plan that is about to be carried out by the body. The person might go to some place where the others cannot see him. He might climb a banana tree to get a banana. But while doing this, he might fall off the tree and hurt himself. If he does not return to the group, his peers know where to look for him. They know what he was about to do or rather in this case where he had gone. This information will help in locating him faster in case of an accident. Otherwise his peers would have to look everywhere in order to find him. This is clearly important and provides an evolutionary advantage.

Let us consider a second example. If one person goes into the woods to get something, he might spot a dangerous animal like a tiger. He could then run back to his peers and say something like "I have seen a tiger approaching the camp." Again, this provides an evolutionary advantage because his peers are warned and are able to take precautionary actions like fleeing or preparing for a fight. He will also be able to tell whether he has found food and whether there is more where he found it so that others may get it too.

III. THE EVIDENCE FOR ADD-ON OF CONSCIOUSNESS

The ability to communicate provides an evolutionary advantage. What is the evidence that consciousness (or rather our communication center) is an add-on? Experiments conducted by Libet et al. (1983)) have shown that the experience
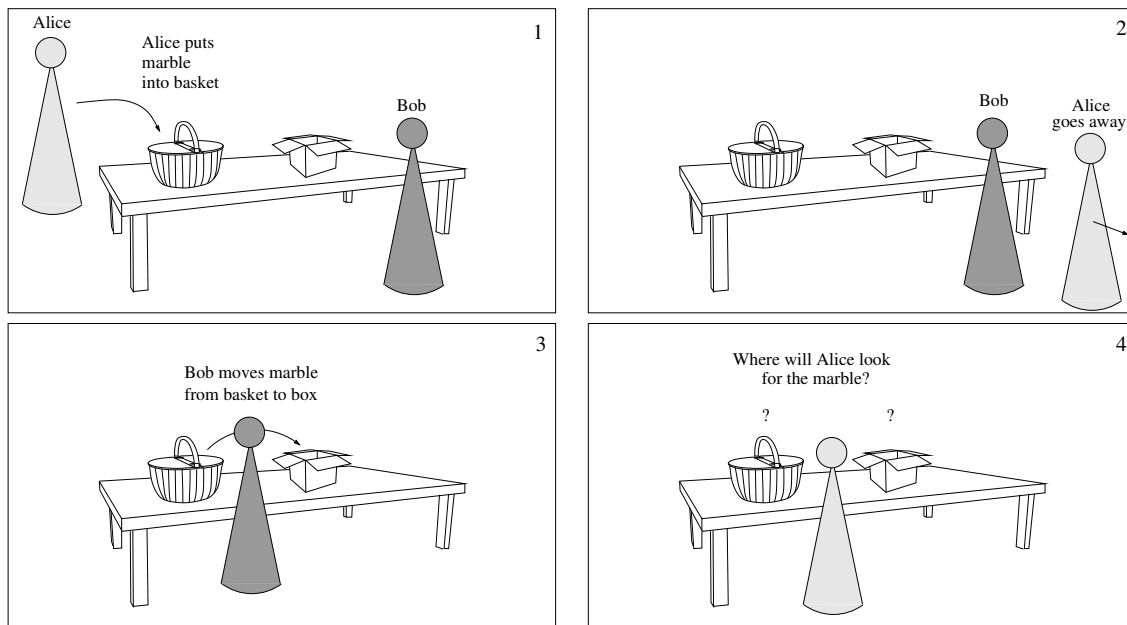
Fig. 1. Theory of mind mechanism is developed in children by the age of about 4 years (Leslie, 1994)).

of conscious will occurs after a readiness potential can be measured. Participants were asked to perform a self-initiated move of a finger. Libet et al. were able to measure the onset of a readiness potential some 500ms before the finger actually moved. On average, participants were aware of wanting to move the finger some 200ms before the finger moved. They were aware of moving the finger approx. 90ms before the finger moved. Apparently, the sequence of events is (1) we are able to measure a readiness potential in the brain, (2) then we are aware of wanting, (3) then we are aware of moving and (4) then the finger moves. This may seem puzzling at first sight. How can we measure that the finger is about to be moved before the person has consciously planned to move the finger? The answer to this is quite simple. The brain creates plans and carries them out and we only become consciously aware of it after the fact. This is not surprising at all assuming that conscious processing requires a sufficiently complex amount of computation. Hence, by the time the computation is complete, a readiness potential can be measured.

According to Wegner (2002)), experience of will is merely a feeling that occurs to a person and conscious will is an experience, not a cause. Wegner lists several reasons for this view. Among them are the experiments conducted by Libet et al. as describe above. Apparently, a small (ca. 30s) time window prior to an action exists. If an action is to be felt as willed, it has to appear within this time window. Graziano et al. (2019)); Graziano (2020)) also argues in the same direction. The brain/person only believes to have subjective conscious experience. This experience arises due to the self descriptive models built by the brain.

The theory-of-mind mechanism (Leslie, 1994)) also supports this view. Humans are able to perceive mind and causal agency in others. When we observe other people or animals we are able to take their point of view (Fig. 1). If we look at an inanimate object such as a piece of rock on the street, we know that it does not have a mind of its own. Let us consider two persons, Alice and Bob. Both are located in front of a table. Alice may put an object into a basket container. Bob witnesses this action. Then Alice leaves the room and Bob moves the object from the basket to the box without Alice noticing this. If one is questioned where Alice will look for the object, it is clear that Alice will look for the object inside the container she originally put the object, i.e. for this example she would look into the basket. We are able to recall the state of mind Alice is in once she has returned and can use this information to tell where she will search for the object. Children are able to attribute the false belief to Alice and are able to predict her behavior by about 4 years. This theory-of-mind mechanism may also be at work in determining causal agency in our own body. Graziano et al. (2019)) also suggest that the human claim to have a conscious mind depends on the theory-of-mind network.

Split brain experiments show that one half of the brain seems to interpret what the other half is doing (Gazzaniga et al., 1977; LeDoux et al., 1977; Gazzaniga, 1989, 1995, 2014; Wolman, 1995)). Gazzaniga and LeDoux (1978)) conducted experiments where they showed an image composed of two parts (left half one scene | right half another scene) to a person whose corpus callosum had been cut. The corpus callosum provides long range connections between the left and right hemispheres of the brain. For instance, a snow scene (a house and a car covered by a lot of snow) could be seen on the left hand side and a chicken claw could be seen on the right hand side Fig. 2(b). What is seen inside the left visual field is fed into the right hemisphere of the brain and what is seen inside the right visual field is fed into the left hemisphere of

the brain Fig. 2(a). The retinal receptors measure the incident light. The axons of the retinal receptors send their signals to the lateral geniculate nucleus (Zeki, 1993; Tovée, 1996)). On the way to the lateral geniculate nucleus, the axons from the left eye covering the right visual field remain within the left hemisphere while the axons from the right eye covering the right visual field cross over to the left hemisphere. In other words, what happens in the right field of view is fed into the left hemisphere of the brain. Similarly, information from the left visual field is fed into the right hemisphere of the brain.

The snow scene is processed by the right hemisphere while the chicken claw is processed by the left hemisphere. The person was given another set of images and was asked which images fit the visual scene. The left hand is controlled by the right hemisphere, while the right hand is controlled by the left hemisphere. The subject picked the shovel with the left hand and the chicken with his right hand. The shovel is an excellent match for the snow scene. It can be used to get rid of the snow and provide easy access to both the house and the car. The chicken is also a good match for the chicken claw. Then the subject was asked why he had made this choice. The person said that the chicken is an obvious fit for the chicken claw. With respect to the shovel the subject said that it is useful to clean out the chicken shed. What happened here? Well, the two hemispheres of the brain were not able to exchange information because of the cut corpus callosum. The language center is located inside the left hemisphere. It had access to the chicken claw and was therefore able to select the chicken with the right hand. However, the language center did not have any information about the snow scene. Apparently, the language center simply made up a plausible story on why the shovel had been chosen.

This points to an after the fact mechanism, i.e. the body behaves in a certain way or performs a certain action and the language area creates an interpretation of why and what was performed. Even well learned actions seem to be stored and accessed in association with their verbal symbolic codes (Franz et al., 2000)). This also points to a mapping between the two, i.e. language and action. Even though callosotomy leads to a breakdown of functional integration ranging from perception to action, this breakdown is not absolute. Response selection and action control seem to remain unified (de Haan et al., 2020)). Essentially conscious perceptual processing is affected most while some information such as good continuation of lines, apparent motion required for unconscious immediate processing is not affected. This may be the result of subcortical (unconscious) processing.

Experiments where people take ownership of rubber hands also support this view. Ehrsson et al. (2004)) placed a life-sized rubber hand in front of the subject where the hand would normally rest. The subject's real hand is hidden beneath a table or similar obstruction where it cannot be seen. Tactile stimuli are applied (using two paintbrushes) to both, the rubber hand as well as the subject's real hand Fig. 3(a). When the brush strokes are applied in synchrony, most subjects have the experience that the rubber hand is their own hand. They take ownership of the rubber hand and "feel" that the rubber hand senses the touch. According to Ehrsson et al. multi-sensory integration in a body-centered reference frame is the underlying mechanism of self-attribution. Ehrsson et al. (2007)) provided neurophysiological evidence that the rubber hand is incorporated into a central representation of the body. They used fMRI to measure anxiety levels of a person when the rubber hand was threatened with a needle (Fig. 3(b)). Subjects experienced an urge to withdraw the hand when it was threatened. Again, this points to a consciousness as a kind of interpreter of what is happening.

IV. QUALIA

But what about Qualia? Qualia is a term that is used to refer to instances of subjective, conscious experience (Chalmers, 1996)). Chalmers asks "Is the character of a phenomenal information space settled by the structure of the space?" With this contribution, I am arguing that this is indeed the case for color. Given that it is the case for the quale "color", it is very likely that this also holds for other types of qualia.

The seemingly hard problem of consciousness is the problem of explaining why subjective conscious experience exist. However, Qualia is nothing mysterious. Our subjective conscious experience is comparable across individuals because we are a product of evolution (Darwin, 1996; Dennett, 1995)). Even though each brain is unique, its "software" or rather "wetware" is similar. Subjective, conscious experience is grounded in reality and we use it to communicate with each other. In other words, there is no hard problem of consciousness (Tomasik, 2015)). The view that conscious states of the brain have an adaptive relationship to our surrounding is also shared by Tononi (2004)).

Let us address color perception first. Researchers in the area of consciousness frequently assume that it is impossible to know how a certain person experiences colors. Is the "redness" that I experience when I look at a ripe strawberry the same "redness" that you experience when you look at the same piece of fruit? Colors, like other perceptions, appear to be, at first sight, subjective experiences. Philosophers might argue that my experience that I have when I look at a strawberry and perceive "red" corresponds to the experience that you have when you look at leaves of a tree and experience "green" and vice versa. I.e., when I look at green leaves, I actually have the same perception that you have when you look at a red strawberry. I will argue below, that this type of red/green exchange is physically impossible. Color perception is comparable across individuals. The perception I have when I see a "red" object is the same perception that you have when you see a "red" object. This is a necessity because you and I are embedded into the same environment and we perceive the same object. We talk about the same object. So why is color perception comparable across individuals? It is comparable because humans estimate reflectance when looking at objects (Ebner, 2007)). Reflectance is a physical quality of the world. What we experience (the quale color) is the mathematical
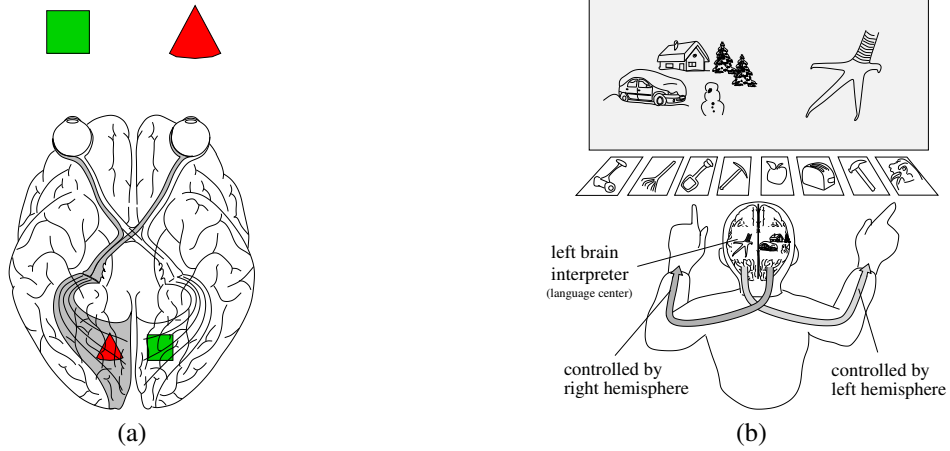
Fig. 2. (a) Information from the right visual field is processed by the left hemisphere of the brain while information from the left visual field is processed by the right hemisphere. (b) A subject with a cut corpus callosum is shown a snow scene in the left visual field while a chicken claw is shown in the right visual field (Gazzaniga and LeDoux, 1978)).
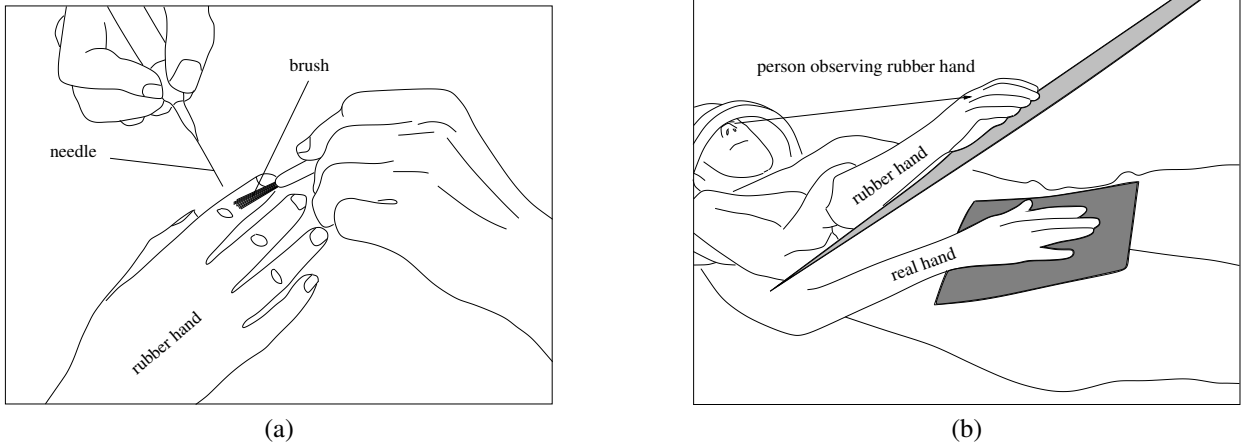

Fig. 3. (a) Brush strokes are applied to a rubber hand by an experimenter. The rubber hand is also threatened with a needle. (b) Experimental set up. The rubber hand is placed inside the field of view while the real hand is hidden (Ehrsson et al., 2007)).

structure of the space of reflectance as represented inside our brains.

We all (with some exceptions) have three kinds of receptors for color perception in the retina (Dowling, 1987; Zeki, 1993; Tovée, 1996)). The cones respond to light in the red, green and blue parts of the spectrum. The cones measure light that is reflected from an object. Unfortunately, this light varies with the illuminant. We can model the measurement made by the cones (Ebner, 2007, 2012)). Let $S_i(x, y, \lambda)$ be the absorbance curves of cone type i with $i \in \{\text{red}, \text{green}, \text{blue}\}$ at position (x, y) of the retina. The sensitivities are shown in Fig. 7(a). Let $L(\lambda)$ be the energy emitted by the light source for wavelength λ. Some of the light is absorbed by the surface while the remaining light is reflected by the object. Let $R(x, y, \lambda)$ be the amount of light for wavelength λ that is reflected by the surface which is imaged at position (x, y) of the retina. This reflectance function can be measured for any given object. Fig. 4 shows idealized reflectance functions of three different objects. Objects with a surface that is described by reflectance function $R_r(\lambda)$ appear red to an observer. Objects

with reflectance function $R_g(\lambda)$ appear green and objects with reflectance function $R_b(\lambda)$ appear blue to an observer. Fig. 5 shows reflectance functions of three color patches from an IT8 calibration target. Actual reflectance functions are of course not as steep as the ones shown in Fig. 4.

Assuming a Lambertian surface which reflects light equally in all directions, then the measurement $c_i(x, y)$ of cone i at position (x, y) of the retina is given by (Ebner, 2007, 2012))

$$c_i(x, y) = G(x, y) \int S_i(x, y, \lambda) R(x, y, \lambda) L(\lambda) d\lambda. \quad (1)$$

We will also refer to this measurement of the cones as

$$\mathbf{c}_{\text{Cone}} = [c_r(x, y), c_g(x, y), c_b(x, y)]. \quad (2)$$

Let us simplify this equation by assuming that each sensor i responds only to a single wavelength λ_i. The cones of course do not have a narrow band response. But suppose we had such a type of sensor. Then we obtain

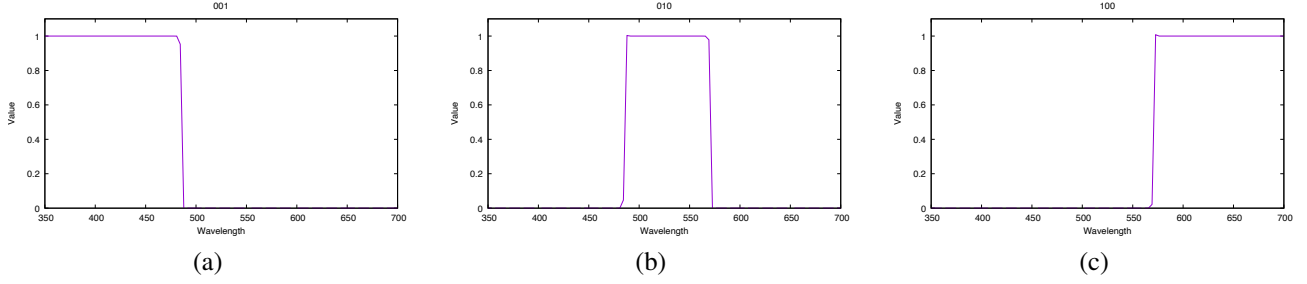$$c_i(x, y) = G(x, y) R_i(x, y) L_i \quad (3)$$

Fig. 4.   (a) Reflectance function $R_b(\lambda)$ (b) reflectance function $R_g(\lambda)$ (c) reflectance function $R_r(\lambda)$.
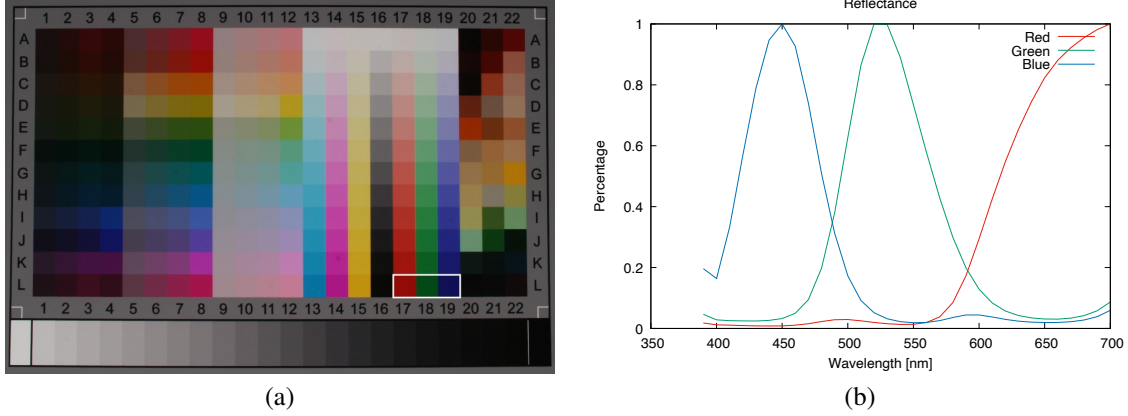

Fig. 5.   (a) IT8 calibration target made by Wolf Faust (www.coloraid.de) (b) Normalized reflectance function of patches L17, L18, L19.

where $R_i(x, y)$ is the reflectance of the object whose light is reflected onto position (x, y) of the retina for wavelength λ_i and L_i is the energy emitted by the light source for wavelength λ_i. For a non-uniform illuminant, we obtain

$$c_i(x, y) = G(x, y)R_i(x, y)L_i(x, y). \qquad (4)$$

Hence, the retinal sensors are only able to measure the product between the illuminant $\mathbf{L}(x, y) = \{L_r(x, y), L_g(x, y), L_b(x, y)\}$ and the reflectance $\mathbf{R}(x, y) = \{R_r(x, y), R_g(x, y), R_b(x, y)\}$. Unfortunately, the illuminant varies throughout the day. The color distribution of daylight depends on the time of day.

Fig. 6 illustrates this process. An image consisting of several differently colored patches is illuminated by four types of illuminants. The original image is shown on the left hand side. Also shown are the spectral color distributions of four illuminants. The cone responses are also shown. The cone responses vary with the illuminant. These measurements cannot be used for object recognition. Only edge information would be useful. However, color is an important cue in nature. Color can be used to identify ripe fruit on a tree (cherries, apples) or in a field (strawberries). In order make use of color information, one has to estimate the spectral reflectance distribution of the object. What we refer to as "color" is essentially an estimate of reflectance. Color is a product of the brain. Cells in visual area V4 of the visual cortex have been found to correlate with reflectance of viewed objects (Zeki, 1993, 1999; Zeki and Bartels, 1999)). On the right hand side of Fig. 6, we see the color estimated by neural processing that simulates the response of cells in V4.

Reflectance could be computed easily if the spectral power distribution of the irradiance at each object position were known. If $L_i(x, y)$ is known, then we can divide the measurement $c_i(x, y) = G(x, y)R_i(x, y)L_i(x, y)$ by $L_i(x, y)$ to obtain the product of $G(x, y)R_i(x, y)$. Given a frontally oriented surface with $R_i(x, y) = 1$ with $i \in \{r, g, b\}$, i.e. a uniformly maximally reflecting surface (in other words a white surface), then $c_i(x, y) = L_i(x, y)$ is an estimate of the illuminant at that point. This method is known as the white patch algorithm. Another option is to average over a sufficiently large number of measurements for different objects (Buchsbaum, 1980)). Assuming that the object reflectances $R_i(x, y)$ are evenly distributed in the range $[0, 1]$, then the average reflectance $E[R]$ will be $\frac{1}{2}$. If $G(x, y) = \cos\alpha(x, y)$ where α is the orientation of the surface to the viewer, then the average $E[G]$ of a number of such surfaces with $\alpha \in [0, 1]$ will be approximately 0.84. Assuming that surface orientation is independent from surface reflectance, we obtain for a uniform illuminant L_i

$$\sum_{x,y} c_i(x, y) = \sum_{x,y} G(x, y)R_i(x, y)L_i \qquad (5)$$

$$= E[G]E[R]L_i = \frac{0.84}{2}L_i \qquad (6)$$

Thus, the illuminant can be estimated by averaging over the measurements from the retinal receptors: $L_i = f \sum_{x,y} c_i(x, y)$
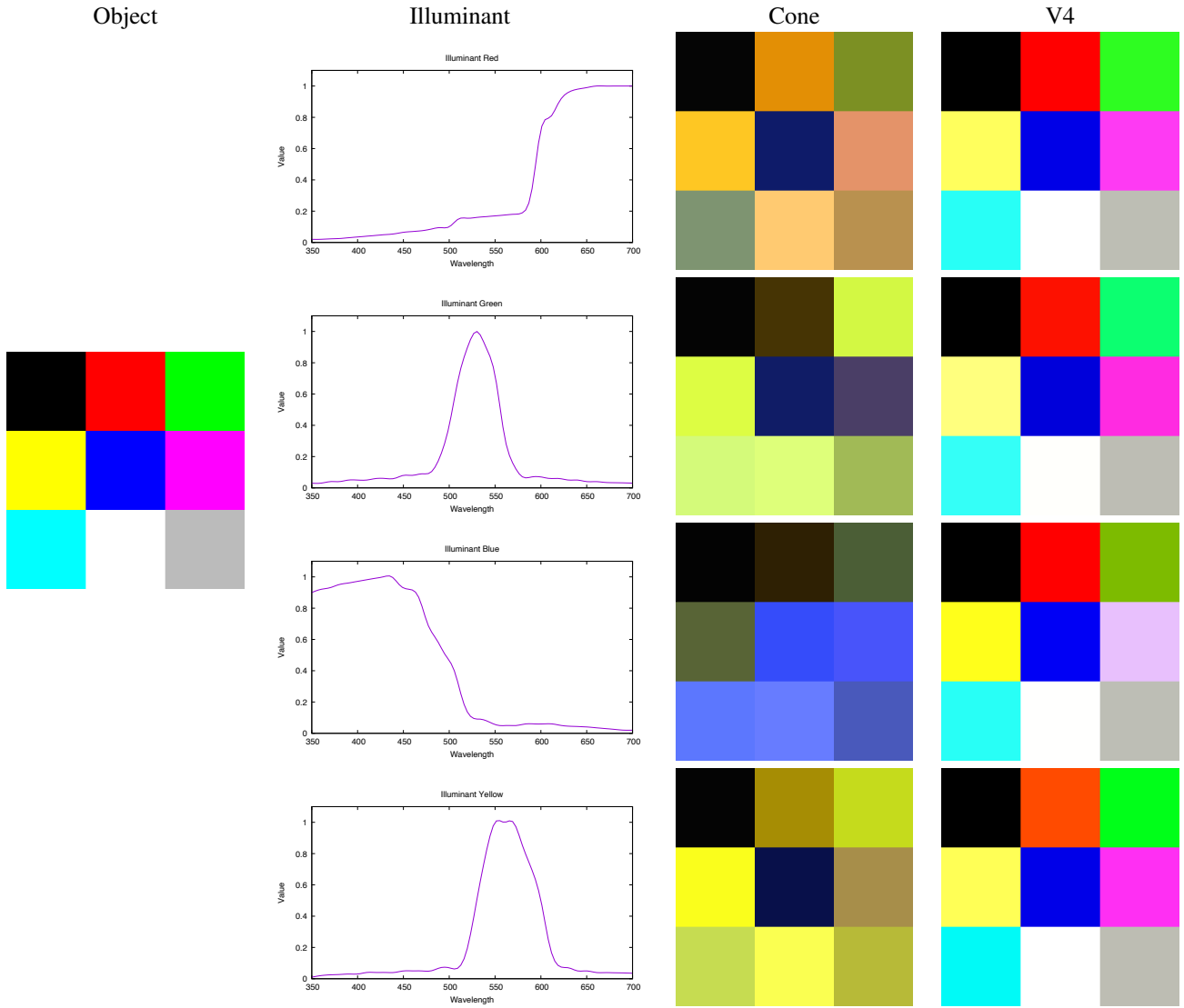
Fig. 6. A color Mondrian is illuminated by several different illuminants. The original image (reflectance data) is shown on the left. The second column shows four illuminants (reddish, greenish, blueish and yellowish). The third column shows that the cone receptors measure. The last column shows an estimate of reflectance. This estimate is computed using only the data measured by the cones by simulating the neural processing up until V4.

for some constant f. A simple rescaling of the measurement c_i after division by $\sum_{x,y} c_i(x,y)$ suffices to remove the constant factor. This is known as the gray world algorithm (Buchsbaum, 1980)). If we average locally, we estimate the illuminant locally for each pixel, i.e.

$$L_i(x,y) = f \int g(x,y)c_i(x,y)dxdy \qquad (7)$$

for some kernel function $g(x,y)$ (Ebner, 2007)). A Gaussian function works fine.

Instead of using the average over all measurements or just the maximum per band, one can also estimate the illuminant from edge information (van de Weijer and Gevers, 2005; van de Weijer et al., 2007; Cheng et al., 2014)). The expected absolute value of color differences across color boundaries

$$E[|R_i(\text{patch1}) - R_i(\text{patch2})|] \qquad (8)$$

is also a constant. Let $R_i(\text{patch1})$ be a uniform random variable describing the reflectance of patch 1 and $R_i(\text{patch2})$ be a uniform random variable describing the reflectance of the second patch then we obtain $E[|R_i(\text{patch1}) - R_i(\text{patch2})|] = \frac{1}{3}$ for $R_i \in [0,1]$. Thus, color differences may as well be used to estimate the illuminant because color differences, shading and illumination are all independent.

All of these methods can be summarized by the following computation (van de Weijer et al., 2007)):

$$L_i(x,y) = f \left(\int \left| \frac{\delta^n}{\delta \mathbf{x}^n} c_i^\sigma(\mathbf{x}) \right|^p d\mathbf{x} \right)^{1/p} \qquad (9)$$

where c_i^σ is an image smoothed with a Gaussian with standard deviation σ and $\mathbf{x} = (x,y)$. For $p = 1$ and $n = 0$ this method is equivalent to the gray world algorithm. For $p = \infty$ and $n = 0$ this method is equivalent to the white patch algorithm. We obtain the gray edge algorithm for $n = 1$. Instead of

smoothing image pixels (or derivatives of image pixels) over an extended area, one may also select pixels or derivatives based on certain criteria. This is what artificial neural net or similar learning based approaches are able to do (Cheng et al., 2015; Bianco et al., 2015; Barron, 2015; Bianco et al., 2015, 2017)).

If the illuminant $\tilde{L}_i(x,y) \approx L_i(x,y)$ is approximated correctly, then we can compute a color corrected output image $o_i(x,y)$:

$$o_i(x,y) = c_i(x,y)/\tilde{L}_i(x,y) \tag{10}$$
$$= G(x,y)R_i(x,y)L_i(x,y)/\tilde{L}_i(x,y) \tag{11}$$
$$\approx G(x,y)R_i(x,y) \tag{12}$$

Algorithms that compute an output image that is independent of the illuminant, i.e. a shaded reflectance image are known as color constancy algorithms in the computer vision community (Ebner, 2007)). Color constancy algorithms work well given narrow band receptors or alternatively if narrow band light sources are used to display the color corrected images. If this is the case, then a simple rescaling of the color channel suffices to remove the influence of the illuminant. However, the above methods are not directly applicable to the human visual system because the cone sensitivities are not narrow band.

Fig. 7(a) shows the cone sensitivities. The three curves overlap considerably. For instance, it is quite impossible to excite the cone in the middle which responds to the green part of the spectrum without also exciting at least one other cone. This overlap makes it difficult to uniquely classify colors. In order for our visual system to be most useful to the organism it needs to estimate reflectance. We have three types of cones that respond to incoming light to various degrees. Therefore, we have three degrees of freedom to estimate reflectance. Our color constant descriptor $\mathbf{c}_{V4}$ that is presumably computed in V4 is essentially a three component vector that can be mapped back to describe the reflectance function of an object in view. Let $\mathbf{M}^{-1}$ be this mapping and let $\mathbf{d}$ be scale factors of reflectance basis functions. Then we have $\mathbf{d} = \mathbf{M}^{-1}\mathbf{c}_{V4}$. Note that this is just a high level mathematical model describing the underlying processing done by the neural architecture. The entire process carried out by the neurons very likely consists of multiple stages until a color is given a label (D'Zmura and Lennie, 1986; Dufort and Lumsden, 1991; Gegenfurtner, 2003; Akbarinia, 2017)).

Fig. 7(b) shows three basis spectral functions to describe object reflectance overlaid on top of the cone sensitivities. These basis functions $R_i(\lambda)$ with $i \in \{r,g,b\}$ were found using optimization. The three component vector $\mathbf{d}$ describes the strength of the respective reflectance function. The overall reflectance function of the object is then given as

$$R(\lambda) = d_r R_r(\lambda) + d_g R_g(\lambda) + d_b R_b(\lambda). \tag{13}$$

The boundaries (where one function transitions to the next) of the three reflectance basis functions are positioned such that the colors red, green, blue excite one receptor strongly and the other two hardly at all, and for the colors yellow, cyan and magenta two receptors are maximally excited while the third receptor is hardly excited. Let c_1 be the response of the receptor that responds maximally, let c_2 be the response of the receptor that has a mid range activation and let c_3 be the response of the receptor that has the lowest activation. The objective function (maximization) was the sum of $c_1 - c_2$ for red $\mathbf{d} = [1,0,0]$, green $\mathbf{d} = [0,1,0]$ and blue $\mathbf{d} = [0,0,1]$ and $c_2 - c_3$ for yellow $\mathbf{d} = [1,1,0]$, cyan $\mathbf{d} = [0,1,1]$ and magenta $\mathbf{d} = [1,0,1]$. The resulting basis functions are the ones shown in Fig. 7(b). They are exactly the same as the ones shown in Fig. 4.

Given the response of the cones $c_i(x,y)$, we would like to compute $\mathbf{c}_{V4}$ and thereby obtain a description of the object reflectance function via the components $\mathbf{d}$. Fig. 8(b) shows the response of the cones to a color image consisting of the 9 different color patches (black, red, green, yellow, blue, magenta, cyan, white and gray) under a white illuminant (flat spectrum). The color descriptors are shown in Fig. 8(a). Tab. 9 lists the actual responses of the cones. For a green object, the cone responding mainly to light in the red part of the spectrum is also excited. For an object with a color of cyan, all three receptors are excited. Classifying colors based on the cone measurements is quite difficult even without the influence of an illuminant.

However, the visual system processes the data measured by the cones using a color opponency mechanism (Tovée, 1996)). Such color opponent cells are found in the retina (Yin et al., 2009)), the lateral geniculate nucleus and area V1. Color opponent cells respond mostly to one type of cone in the center while activation of another type of cone inhibits the cell. This allows the cell to compute color differences. Double opponent color cells also exist. Double opponent color cells combine the output of two types of color opponent cells. The cone measurements can be considered as measurements along a three axis coordinate system (red, green and blue). Each component describes the presence or absence of light in the red, green or blue parts of the spectrum. However, these measurements do not correspond to reflectance. The color opponent cells transform the coordinate system to a coordinate system with the three axes: dark-bright, red-green, blue-yellow. This is frequently modeled as an addition of all three channels for the dark-bright channel, as a subtraction between red and green for the red-green channel and as an addition of red and green and a subtraction of blue for the blue-yellow channel (Akbarinia, 2017; Ebner, 2007, 2012)).

$$\mathbf{c}_{Op} = \begin{bmatrix} \text{achromatic} \\ \text{red} - \text{green} \\ \text{yellow} - \text{blue} \end{bmatrix} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & -1 & 0 \\ 0.5 & 0.5 & -1 \end{pmatrix} \mathbf{c}_{Cone} \tag{14}$$
$$= \mathbf{M} \cdot \mathbf{c}_{Cone} \tag{15}$$

Several different variants of this transform have been proposed (Pridmore, 2020; Gao et al., 2013)). Within this coordinate system, color can now be processed independently from brightness information. Only two of the components contain color information. This transformation can be considered as a rotation of the coordinate system (Land, 1986)).
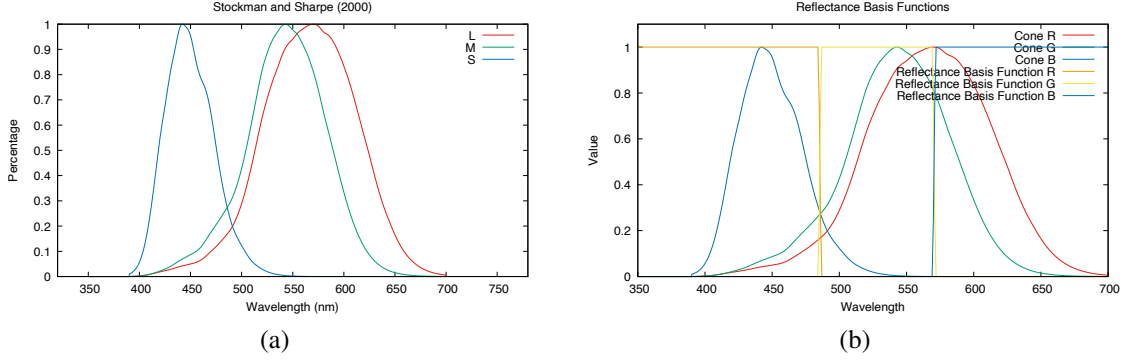
Fig. 7. (a) Cone sensitivities. Data from Stockman and Sharpe (2000)). (b) Optimized reflectance basis functions.
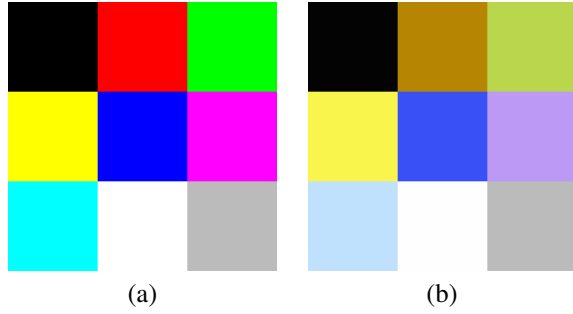

Fig. 8. (a) Color descriptors for 9 different colored patches. (b) Cone response to the different object patches shown on the left.

Color Name	$\mathbf{d}$	$\mathbf{c}_{\text{Cone}}$
black	$[0, 0, 0]$	$[0.01, 0.01, 0.01]$
red	$[1, 0, 0]$	$[0.47, 0.24, 0.01]$
green	$[0, 1, 0]$	$[0.49, 0.68, 0.08]$
yellow	$[1, 1, 0]$	$[0.96, 0.92, 0.08]$
blue	$[0, 0, 1]$	$[0.04, 0.08, 0.92]$
magenta	$[1, 0, 1]$	$[0.51, 0.32, 0.92]$
cyan	$[0, 1, 1]$	$[0.53, 0.76, 1.00]$
white	$[1, 1, 1]$	$[1.00, 1.00, 1.00]$
gray	$[0.5, 0.5, 0.5]$	$[0.50, 0.50, 0.50]$

Fig. 9. Color names and corresponding cone responses. Minimum cone response is 0.01. This limit is used to model sporadic firing.

Apart from separating color from brightness information, estimating reflectance becomes easier within the rotated coordinate system. The two components red and green become untangled. Suppose for a moment, that $\mathbf{c}_{V4}$ uses a coordinate system with axes dark-bright, red-green, blue-yellow where $[*, 0, 1]$ corresponds to "red", $[*, 1, 0]$ corresponds to "green", $[*, 0, 0]$ corresponds to "blue" and $[*, 1, 1]$ corresponds to "yellow". Colors within this coordinate system can be classified a lot easier than the cone responses shown in Tab. 9.

The function of color opponent cells have also been modeled to develop color constancy algorithms (Gao et al., 2013, 2015; Akbarinia, 2017)). Indeed, the transformation carried out by the color opponent cells are quite helpful for estimating reflectance. As explained above, we can simply rescale all color bands independently using the maximum excitation per

color channel if the receptors are quite narrow band. Then we can obtain an estimate of $\mathbf{d}$, i.e. the scale factors of reflectance basis functions. The result is shown in Fig. 10. This method works well if the receptors are narrow band. The mean squared error between the output and the estimate of the scale factors of reflectance basis functions is very small (0.006) in this case. Rescaling does not work well if the receptors are relatively broad band (mean squared error of 2.327). If the cone measurements are transformed using matrix $\mathbf{M}$ and then a rescaling operation is applied, the mean squared error drops to 1.094.

We can also use artificial evolution to search for a suitable color transform. A (100,500) evolution strategy (Rechenberg, 1994; Schwefel, 1995)) with step size adaptation was used to optimize all 9 parameters of the color transformation matrix $\mathbf{M}_{\text{evo}}$. A single step size parameter was used for all 9 parameters. The parameters used to perform this optimization are shown in Tab. 11. The optimization function is the mean squared error between $\mathbf{M}_{\text{evo}}^{-1}\mathbf{c}_{V4}$ and the ground truth reflectance scaling factors for the patch shown in Fig. 8(a). The root mean squared error was computed over 5 illuminants (white, red, green, blue and yellow). The best result of this optimization (10 runs) is the following matrix.

$$\mathbf{M}_{\text{evo}} = \begin{pmatrix} 0.178 & -0.140 & -1.985 \\ -0.993 & 1.475 & -0.025 \\ -1.606 & 1.988 & -0.027 \end{pmatrix} \quad (16)$$

This matrix also features red-green color opponent behavior. The mean squared error drops to 0.619. This shows that color opponent computation helps in computing reflectance scaling factors. In nature, the fitness function is of course given via survival. Individuals capable of estimating reflectance are more fit to find ripe fruit and therefore have higher chances of survival.

Once the visual system is capable of estimating the reflectance function for various objects, language is able to assign a label to the different reflectance functions as shown in Fig. 9. Parsimonious ellipsoids might be used to classify the response of neurons in V4 and thereby attach color names to different responses of these neurons (Akbarinia, 2017)). The color labels shown in Fig. 9 are reflectance function descriptors
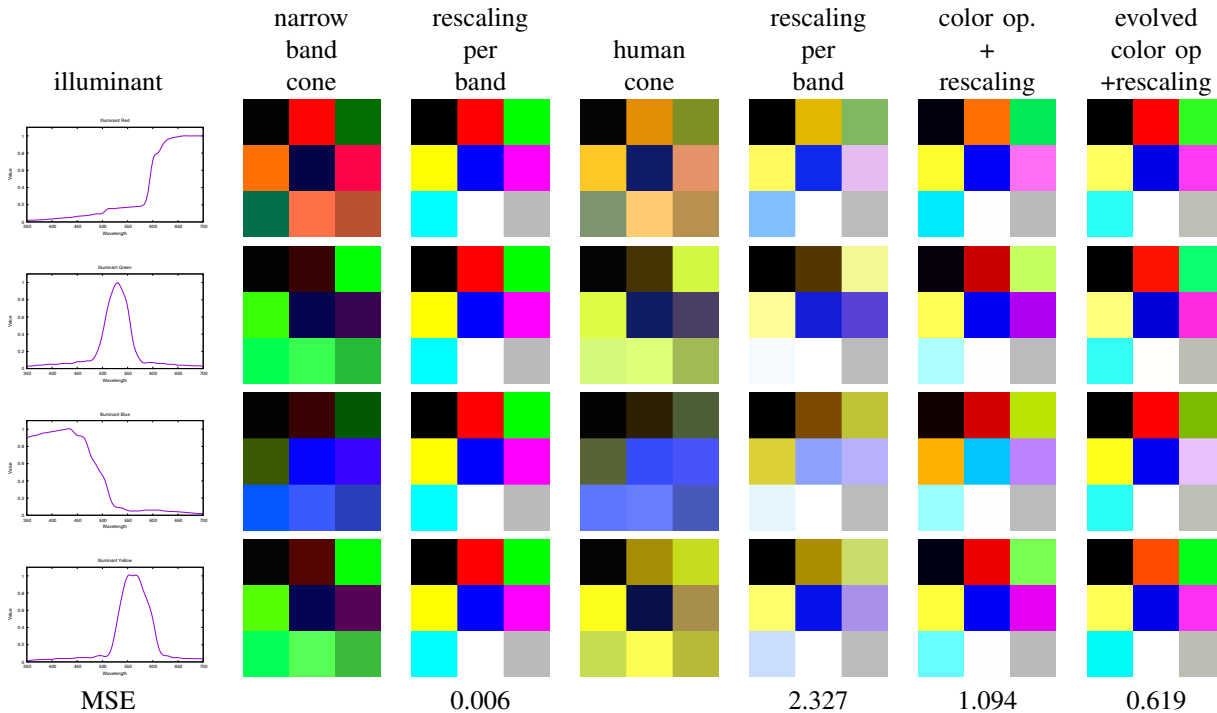
Fig. 10. A checkerboard pattern from Fig. 8(a) is illuminated by four different illuminants (left column). The response of narrow band cones to this stimulus is shown in the second column. The third column shows the result of a simple rescaling to the range $[0, 1]$. Rescaling works fine if the spectral sensitivities of the cones were narrow band. However, human cones are not narrow band. In this case, rescaling does not work (columns 4 and 5). Introducing a so called color opponent transformation improves computation of reflectance descriptors (columns 6 and 7). Column 7 shows the result of the reflectance descriptor computation when the color transformation is evolved. At the bottom, the mean squared error between the output and the actual reflectance descriptors are shown.

Parameter	Value
number of parents μ	100
number of offspring λ	500
initial value of step size τ	0.01
number of generations	1000
initial value range x_i	$[-2, 2]$
initial value range δ	$[0.001, 0.1]$
mutation	$N(0, \delta)$
step size adaptation	$e^{N(0,\tau)}$
crossover	two point

Fig. 11. Evolution strategy parameters.

that maximally separate colors (or rather reflectance descriptors) from one another. Of course human color names refer to certain objects of the environment, i.e. ripe fruit. Not all colors are equally important. Human color naming appears to go through a unique sequence with red being the first color after white and black (Berlin and Kay, 1999)). It is likely that colors are added to a language depending on the amount of evolutionary advantage they provide.

Someone might say: "This is a red ball". We assign the label "red" to a reflectance spectrum that reflects most of the light in the red part of the spectrum when viewed under white light. Therefore, color perception is not subjective. It is comparable across individuals because the label "red" corresponds to a physical, objectively measurable quantity of

the world. Given the above, we argue that the experience of one person's "redness" cannot be the same as another person's "greenness". "Red" and "green" cover different parts of the visible spectrum. Therefore, the perceptions for "red" and "green" differ. They don't differ in an arbitrary way. "Red" represents reflecting mostly light in the red part of the visible spectrum while "green" represents reflecting mostly light in the green part of the visible spectrum. Internally, we use a representation based on just three values. A representation of $\mathbf{c}_{V4} = [*, 0, 0]$ corresponds to "red" (object reflects light mostly in the low range of the visible spectrum) and a representation of $\mathbf{c}_{V4} = [*, 1, 1]$ corresponds to "yellow" (object reflects light mostly in the low and mid range of the visible spectrum). A representation of $\mathbf{c}_{V4} = [*, 1, 0]$ corresponds to "green".

Only one question remains. Might it be possible that some persons have an inverted perception of the visible spectrum? Since humans only have three types of receptors, humans are only able to estimate reflectance roughly. The internal representation used by the brain is based on the measurements of the three types of cone receptors. That's why only three types of primary light sources (with the appropriate spectral characteristics) suffice to produce any (or rather most) color sensation. That's why computer monitors or projectors work. That's why we perceive a full color scene that looks perfectly realistic when we go and see a movie.

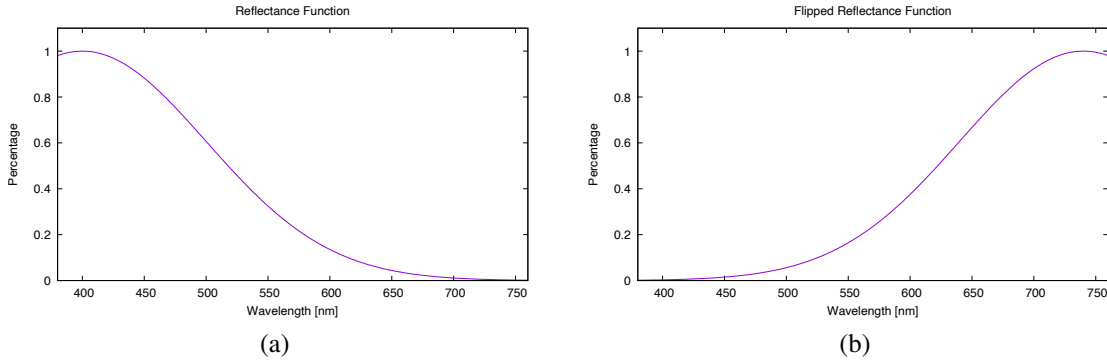So might your experience of $\mathbf{d} = [1, 0, 0]$ correspond to

Fig. 12. (a) Reflectance function $R_1(\lambda)$ (b) flipped reflectance function $R_2(\lambda) = R_1(1140 - \lambda)$. Could it occur that two different observers have the same color perception when looking at flipped stimuli? I.e., observer A has one color sensation when observing R_1 while observer B has exactly the same color sensation when observing R_2.

my experience of $\mathbf{d} = [0, 0, 1]$? The internal representation in our brains describe a one-dimensional function (reflectance). Let us assume for the sake of argument that the visible spectrum ranges from exactly 380nm to 760nm. The wavelength exactly in the middle of this range is 570nm. Theoretically, we could flip the representation of the reflectance function around 570nm. We could hypothesize that one person's internal representation, i.e. "color" of the reflectance function $R_1(\lambda) = \delta(\lambda - 400)$ is identical to the internal representation, i.e. color sensation, when another person is observing an object with $R_2(\lambda) = \delta(\lambda - 740)$ (see Fig. 12). In general, the perception of $R(\lambda)$ of one person would be identical to the perception of $R(760 - (\lambda - 380) = R(1140 - \lambda)$ of another person.

However, this is not possible, because the cone that responds strongly to light in the middle part of the spectrum, the "green" cone, peaks at a wavelength of approximately 530nm. Fig. 9 shows the normalized absorption characteristics. The cone responding to longer wavelengths peaks at approximately 560nm. The cone responding strongly to shorter wavelengths peaks at approximately 420nm. The peaks of the cone responding to light in the middle part of the spectrum and the one responding to light in the long part of the spectrum are quite close to each other. The "green" cone is not placed half way in between the other two cones. Hence, it is impossible to invert a spectrum and then hope to obtain an inversion of the internal representation. This is not possible because the "middle" cone is not centered in between the other two cones.

Chalmers (1996)) posed the question: "Is something with the approximate character of our color experiences the only way that visual color information might have been projected into phenomenology, or is there a different way entirely?" All of the above shows that color perception is not something that is arbitrary and subjective to a person. Color perceptions are comparable across observers (at least those with normal vision) because what we perceive as "color" is the approximation of a one dimensional function (reflectance).

Indeed, our perceptions have been shaped by natural selection (Hoffman et al., 2015)). Using object reflectance instead of the reflected light provides an obvious evolutionary advantage. The reflected light varies with the spectral power distribution of the illuminant whereas the reflectance function does not. Hence, it makes sense to estimate this reflectance function. Humans who are able to reliably recognize ripe strawberries in a field or cherries on a tree are better adapted to their environment and will find more food than others who do not have this ability. The estimate of the reflectance function allows us to guide our behavior in a better way. Hence, the genes of humans who are able to estimate the reflectance function of objects will have better chances of surviving and this trait will dominate future generations.

Now that we understand what we call "color" is an internal representation of a one-dimensional function, one could argue that color perception might not require consciousness. Other kind of perceptions might show that the hard problem of consciousness does exist. This kind of argument is reminiscent of the early days of artificial intelligence research when some abilities like playing chess were assumed to require intelligent behavior. Today, computer programs like Deep Blue or Deep Fritz are able to play like a champion (Nilsson, 2010)). However, these programs do not possess a general form of intelligence. Playing chess is no longer considered a difficult problem. It seems that once a problem has been solved, it is no longer assumed to require intelligent behavior. In consciousness research one could argue that color perception is not a "quale" but other types of perception, object perception, perception of words or feelings like love or pain are. Once one realizes that color perception is not subjective, then a similar argument can be made about other modalities like feelings. Feelings are not arbitrary. They exist and are shared across humans because we have the same evolutionary history (Ekman, 1993; Shariff and Tracy, 2011)). They provide a measurement of the internal state of an individual. Individuals are trying to avoid behavior that leads to pain (Kováč, 2012)). Obviously, individuals that avoid pain have a better chance at surviving and hence reproducing.

As we obtain a better grasp of the processing that is involved in color perception or registration of internal states of an organisms, i.e. feelings, we will see that (over time) the mystery of consciousness slowly disappears. Consciousness arises (as

a necessity) out of the processing that is carried out by the organism. If an artificial machine were to carry out similar processing, then it would also lead to conscious perception of the environment and its internal states. Implications for machine consciousness will be discussed below.

V. Perception of the Environment

When we perceive our environment, we are able to name things. In other words, we attach labels to objects. In this respect, perception works exactly as expected. If we bring a visual stimulus in front of our eyes, we can react to it. We are able to name the object in front of our eyes and we are able to describe its properties. The brain appears to have separate processing paths with respect to action and perception (Milner and Goodale, 2006)). We perceive objects relative to the head with a single screen view Fig. 13(a). That's because we speak about things relative to the head. However, we perceive our environment via two eyes. In theory, humans could look at two different objects at the same time with one eye focusing on one object and the other eye focusing on another object Fig. 13(b). Interestingly, horses seem to be able to see two things at once, i.e. separately with their eyes. If a trainer teaches a horse something, the horse needs exposure to what is being taught twice. Once with the left eye and once with the right eye (Williams, 2004)). Horses communicate vocally and non-vocally with their peers.

The retinal receptors within the eye are not uniformly distributed. Most of the cones are located in the fovea, i.e. the center of the retina. The resolution is much higher in the fovea compared to the periphery. This non-uniform resolution is illustrated in Fig. 14(b). The original input is shown in Fig. 14(a). When the visual information reaches visual area V1, the striate cortex, in the back of the brain, a log polar transform has been applied (Schwartz, 1977, 1980; Cavanagh, 1978, 1984)). The log polar transform of the cone measurements is shown in Fig. 14(c). Because of this transform, a rotation of the object leads to a horizontal shift of the visual information in V1. If the observer moves towards or away from an object, then the visual information in V1 is translated vertically. The log polar mapping leads to a rotation and scale invariant representation of the visual data. This is helpful for visual recognition (Wallace et al., 1994)).

Only a small portion of the visual field is perceived with high acuity at any point in time. The eyes constantly perform saccades (Fuchs, 1967; Land, 1999; Gibaldi and Banks, 2019)). They attend to different aspects of the scene in front of us. Fig. 15(a) shows how the eye attends to different parts the scene. What arrives at V1 is a sequence of images from different parts of the scene. Fig. 15(b) shows the non-uniform measurements of the retinal receptors.Fig. 15(c) illustrates how this data is processed by the brain. The non-uniform measurements are transformed to a log space representation in V1. However, we are not aware of the non-uniform distribution of the retinal receptors in the eye, nor are we aware of the saccades that the eyes perform. Fig. 15(d) shows how the scene is consciously perceived. The scene appears to be

taken with a monocular camera attached to the head. It is a first person view. The scene is perceived relative to the head. We communicate information about what has happened in our environment to our peers. This single screen view is necessary from a communication point of view. If one person were speaking about separate perceptions of the two eyes as illustrated in Fig. 13(b) then this would make communication considerably more complicated.

The single screen view arises as a necessity for any organism with a receptor sensor array that is capable of communicating with its peers. How the sensor array is arranged is irrelevant. Visual perception has to be like this because we are able to call out colors for any small region of our visual field. In theory, we could also perceive our environment like a depth map (Yang and Pollefeys, 2003)) where each point of the visual "screen" represents the distance from the observer's eyes to the object as shown in Fig. 16. However, this is not how we perceive our environment. We are able to estimate distances to every point in our field of view using stereo vision. We are able to tell our peers about distances to various objects inside our field of view. The observed scene appears "three-dimensional" to an observer because again this is how space is structured. Indeed, the perception of the observed scene does not change when one eye is closed. Distances can be estimated using a variety of cues. Stereo vision is only one option to estimate distances. Distances can also be estimated from focus (Nayar, 1992; Favaro and Soatto, 2008)) or from motion parallax (Wexler and van Boxtel, 2005; Rogers, 2009; de la Malla et al., 2016)) to name but a few.

What about auditory experiences? We consciously perceive words or sounds but we are not consciously aware of individual frequencies making up these sounds. We do not perceive these sounds as a bar graph where the height of the bar signals the strength of the frequency as shown in Fig. 17(a). We do not perceive sounds as a dot matrix in our visual field where the brightness or color of the dot signals the strength of the frequency as in a spectrogram as shown in Fig. 17(b). In theory, it would be possible for us to perceive sounds in this way. Actually, humans are able to identify words by looking at a spectrogram (Zue and Cole, 1979)). So why do we perceive sounds or visual input in the way we do? The answer to this question is: Because we use what we consciously perceive in order to communicate with others. We are able to identify things that we hear. It is also language based. We can recognize a wide range of auditory stimuli and react to them. Audio information from our peers is transformed into meaningful words and sentences.

Like color, words and sentences are a product of the brain. When listening to someone speak, we can hear the individual words of a sentence (Dennett, 1991; Studdert-Kennedy, 1981)). It appears as if someone says one word after the other. However, this is not visible in a waveform recording of a spoken sentence. Early approaches in natural language processing tried to recognize short audio sequences and map this information to phonemes which were then mapped to full sentences (Nilsson, 2010)). Modern approaches are based on
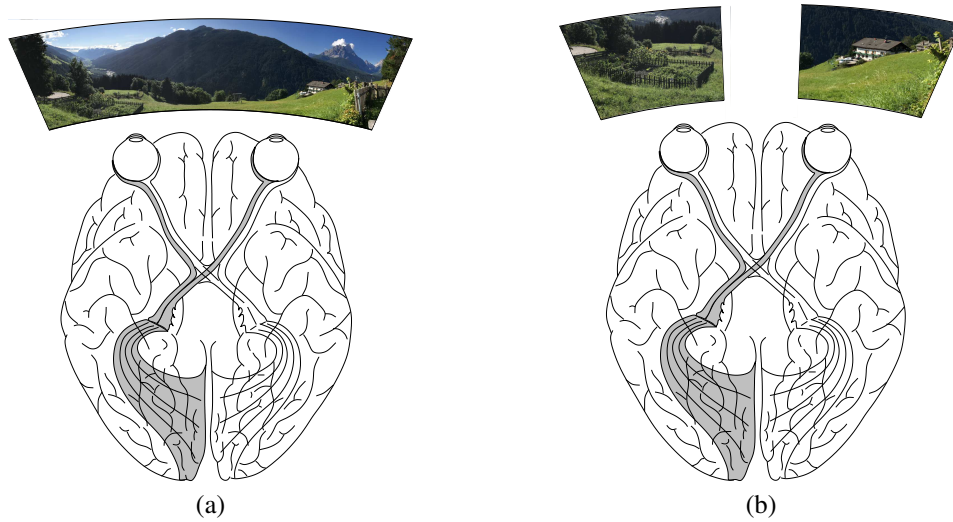
Fig. 13. (a) Single screen view. (b) Two eyes perceiving different parts of the scene.
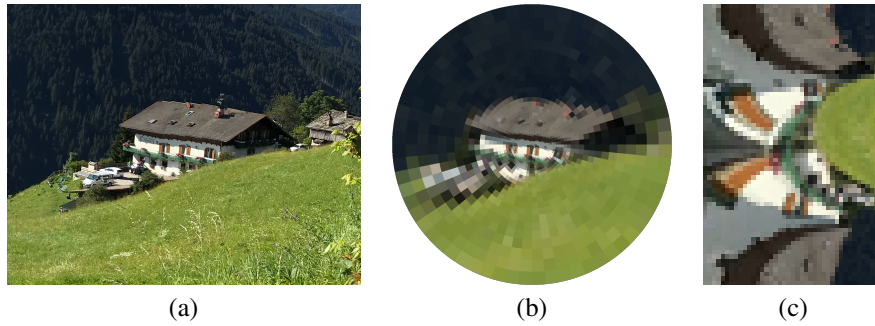

Fig. 14. (a) Visual perception of a scene. (b) Non-uniform measurements by the retinal receptors. (c) Log polar mapping of the data shown in (b).
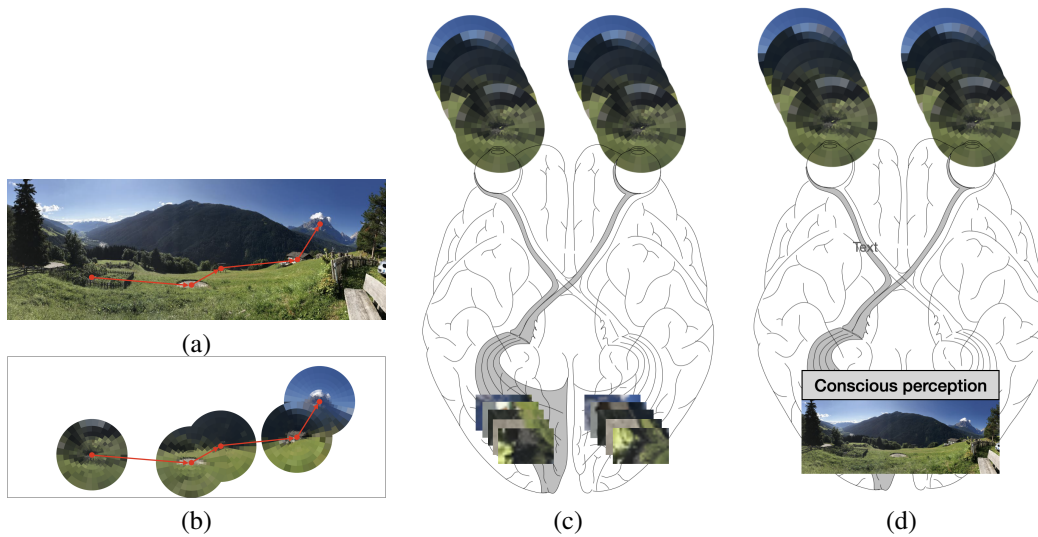

Fig. 15. (a) Visual perception of a scene. The eye constantly executes saccades where the eye jumps from one interesting location to another. (b) Non-uniform measurements by the retinal receptors. (c) Log polar transformation of the sequential data. The right part of the visual field is fed into the left hemisphere and vice versa. (d) Conscious perception. It feels as if a cinematic representation exists.

Fig. 16.   (a) Visual perception of a scene. (b) Depth Map. Pixels that are closer to the camera appear brighter.
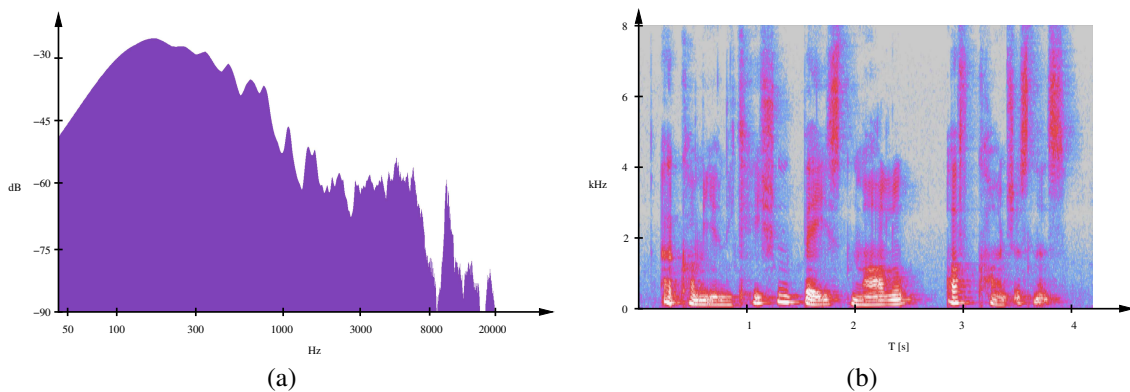

Fig. 17.   (a) Frequency distribution of a short audio sequence. (b) Spectrogram of a short audio sequence. The color of each pixel visualizes the gain of each frequency.

deep convolutional neural networks (Saon et al., 2017; Zhang et al., 2019; Passricha and Aggarwal, 2020)).

VI. CONSCIOUSNESS AND LANGUAGE

Consciousness seems to be intertwined with language. Its primary role is to serve communication between individuals. Qualia exist because being able to communicate them to others provides an evolutionary advantage. We perceive objects within our visual field relative to the orientation of our head. This information is then stored and can also be communicated to others during perception or at a later time. The same holds for the perception of audio as well as feelings, sounds or smells.

The appearance of a mental visual image is a result of the visual information processing. If someone holds a photograph into the visual field of a person then this person can recognize the contents of the photograph. If the photograph shows a particular person, then this photograph mimics the light that is reflected of that particular area much in the same way as if the person were actually standing there. Similarly, if one were to use a projector and project a photograph of a person onto a screen then the pixels on the screen reflect the same light (actually the same relative intensities in the red, green and blue parts of the spectrum) that would be reflected if the person

were actually standing at the position of the screen. This visual mental image arises because we process information relative to the head and we use light responsive sensors to measure incident light. If one is to change the number of different cone receptors, then this has no impact on the general arrangement of the mental visual image. Only the reflectance estimate per "pixel" improves. With a single receptor, one is able to discern brightness differences. With two color receptors, reflectance can be estimated for two function support points. Using three receptors, we have three function support points. The more support points we have, the better we are at distinguishing object reflectances.

Tetrachromats like birds are assumed to have the same mental image as humans except that they can distinguish more "colors" per pixel or, expressed in another way, can determine object reflectance better than humans. Birds have four receptors that are almost uniformly distributed between the range 300 nm and 700 nm. Compared to human vision, birds have an additional receptor which responds in the ultraviolet part of the spectrum. Experiments indicate that birds see ultraviolet wavelengths as distinct colors (Goldsmith, 2006)). In other words, this fourth receptor is used to obtain a better reflectance estimate and birds are able to distinguish more colors than

humans. Thus, four receptors result in four function support points and so on.

Color perception arises out of the necessity to represent information of a two or higher dimensional value (here surface reflectance) per pixel. The quale "color" is a result of the mathematical structure of the problem. Due to the relationship between color and reflectance, color is not arbitrary as shown above. Feelings are also not arbitrary but have a certain purpose. Feinberg (2001)) also suggests that meaning and purpose are created by the brain. Feelings are a product of evolution (Ekman, 1993; Shariff and Tracy, 2011)).

The next obvious question is "Who else is conscious?". According to this theory, any organism capable of communicating with others is a conscious being. Communication is possible using language but also through other means, e.g. bees are known to perform a dance to inform their peers about the direction and distance to flowers (Dyer and Seeley, 1991; Sherman and Visscher, 2002)). They also are able to remember task related information (Koch, 1991)). Some birds have been shown to recognize themselves in a mirror (Prior et al., 2008)) and some are known to use tools (Weir et al., 2002; Holzhaider et al., 2010)) are probably conscious too. Some crows appear to have the cognitive capacity to manufacture objects from a mental template (Jelbert et al., 2002)). Organisms which have no means of communicating are definitely not conscious. However, most organisms are probably able to communicate with their peers in one way or another and are therefore conscious.

VII. Machine Consciousness

Is it possible to build artefacts that are able to consciously perceive their environment? According to the integrated information theory this seems to be possible (Tononi, 2004, 2008)). All of the above points to consciousness being a communication system. So how can we create machine consciousness? It seems that all that is required is an embodied robot. Suppose we add a communication system to such a robot, that is able to communicate future plans and important events that have happened in the past. Such a robot would be indistinguishable from a conscious human being (provided that its communication system would be as elaborate as the human system). The robot needs memory to store (1) intentions or plans, (2) actions (information about where, when, and what did the robot do) and (3) internal as well as external percepts (who, where, when and what happened). The communication system would have access to this memory and would be able to communicate plans, actions and percepts to others. The schematic diagram is shown in Fig. 18(a). Such a robot, equipped with a standard camera, would be able to see colors in much the same way that we do (because the quale color arises out of the three-dimensional space of reflectance function descriptors) provided that the communication system has access to a simulated version of the neurons in V4 as described above.

Many have argued that a recurrent flow of information is important to create consciousness. The human mind can be illustrated as having two feedback loops as shown in Fig. 18(b). A fast acting unconscious control system and a second feedback loop for conscious perception and control. The second loop could be an evolutionary add-on to the existing control loop. It appears that the earliest evolutionary functions of vision were action-oriented and not perception oriented (Milner and Goodale, 2006)).

So where is the difference between the two loops? Both have a recurrent flow of information. With respect to the integrated information theory, one could argue that the second slower loop operates on just the right time scale and contains the neural assemblies that end up having a high value of Φ as defined by the integrated information theory (Tononi, 2012; Oizumi et al., 2014)). Here, it is argued that systems, e.g. artificially built robots, that do not exchange information in a purposeful way are not conscious. It is irrelevant how elaborate the information processing might be. Consciousness requires an exchange of information between individuals. A non-zero Φ is not sufficient to generate consciousness.

The communication system is assumed to be the system (in humans) having the largest value of integrated information theory Φ. A CPU processing the data from simulated V4 using NAND or NOR gates and is able to inform others about this fact, will also perceive colors in the same way as a conscious human being. Of course such a robot would not be able to have feelings like pain, love or hate. We humans have these feelings because of our evolutionary history. Since the robot does not share our evolutionary history, it will not have feelings like pain, love or hate. The ability to experience qualia will remain with someone as long as the neural assembly in charge of processing percepts (the communication center) is able to function. This holds, even if the ability to communicate is destroyed (because the connection to the motor center is severed or if muscles are no longer able to perform their function).

VIII. Review of Existing Theories

Several neurobiological theories of consciousness have been put forward. Kouider (2009)) has reviewed several theories. Humans appear not to be aware of processing which occurs inside the primary visual cortex (Crick and Koch, 1990)). Conscious processing of visual information only happens in higher visual areas. The ventral visual pathway is used for perception whereas the dorsal visual pathway is used for action. This is the duplex vision theory of Goodale and Milner (1992)). Crick (1994)) argues that consciousness depends crucially on thalamic connections with the cortex. According to Aleksander (1996)) the primary function of consciousness seems to be the functional memory of past experience, its integration into a perception of the present and its projection into the future. Gazzaniga and LeDoux (1978)) focus on language. According to their view, the language center or verbal system monitors and registers perceptions, thoughts, moods and actions of its owner. This verbal system creates the personal sense of conscious reality. They also assume that similar memory systems might be in use in nonspeaking
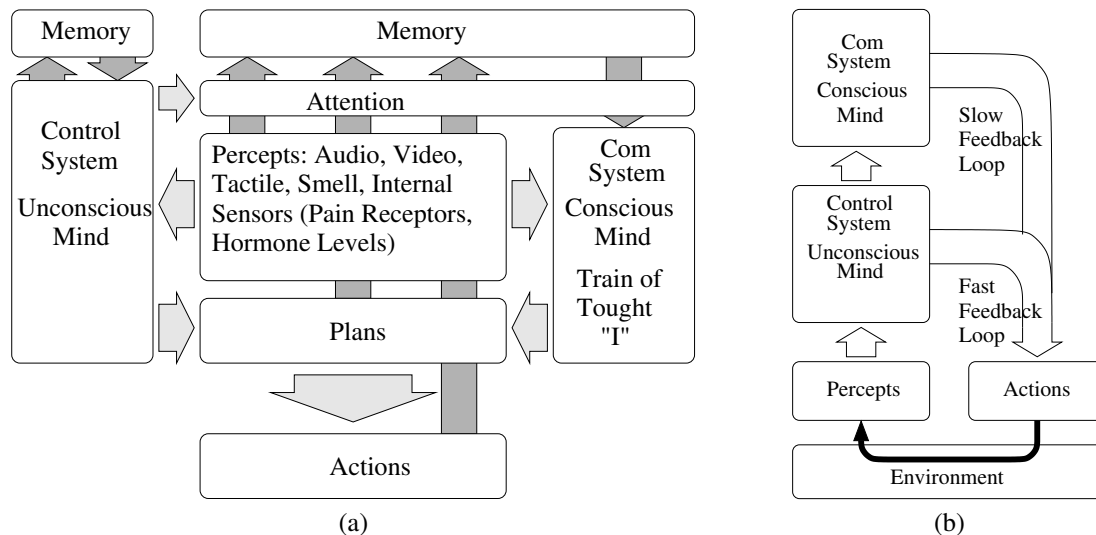
Fig. 18.   (a) Separation between unconscious and conscious processing (b) Two systems are working together. One is an unconscious control system. The second is an add-on used to communicate information. This second feedback loop is slower than the first one.

animals. However, they point out that the human verbal system creates awareness and self-awareness in ways that are unique to humans.

Tononi and Edelman (1998)) have put forward the reentrant dynamic core theory. This theory is based on recurrent processing of information. Damasio (1999)) argues that we become conscious when our organism internally constructs and exhibits a specific kind of wordless knowledge about how the organism's own state is affected by the processing of an object. Damasio calls this type of nonverbal account core consciousness. Memory added to processes that result in core consciousness allow an organism to create an autobiographical record or self. This leads to (as Damasio calls it) extended consciousness. According to Dehaene and Naccache (2001)), consciousness is based on a global neuronal workspace. Dehaene (2014)) suggests that the evolutionary role of consciousness is learning over time as opposed to living in the instant and that consciousness is essentially nothing but the flexible circulation of information inside the global neuronal workspace. Tononi (2004, 2008, 2012)) has developed the information integration theory. His theory is also supported by results on how anesthetics work. It appears that anesthetics block the brain's ability to integrate information. Once integration of information is no longer possible, an organism becomes unconscious (Alkire et al., 2008)). The integrated information theory is being continually improved (Oizumi et al., 2014)). So far, it describes experimental results very well.

Synchronous firing of neurons may also play a role in conscious information processing (Singer, 1999; Ebner and Hameroff, 2015)). Lamme (2006)) created the local recurrence theory which is also based on recurrent information processing. According to Zeki's (2007) micro-consciousness theory, multiple consciousnesses are distributed across different processing sites. These are all neural correlate of consciousness theories. They try to define a minimal set of neuronal events and mechanisms which are sufficient for a conscious percept.

Kotchoubey (2015)) argues that consciousness is a kind of behavior and emerges on the interface between three types of behavior: communication, play, and the use of tools. All of the above theories are not constructive, i.e. they do not provide an algorithmic description of information processing occurring inside a conscious entity. Graziano et al. (2019)) have suggested that a single, coherent explanation of consciousness is available, but has not yet been recognized. They propose a standard model of consciousness that reconciles the attention schema, global workspace, higher-order thought, and illusionist theories.

Penrose has argued that quantum effects are used by the brain for conscious information processing (Penrose, 1989, 1994)) and that no algorithm is able to describe consciousness. Hameroff and Penrose (1996)) proposed a model of consciousness in which orchestrated objective reduction of quantum coherence occurs in brain microtubules. If quantum effects really do play a role in conscious information processing, then we could simulate them on a sequential computer. Even though quantum computing can be simulated on a standard CPU (Williams and Clearwater, 1998)), this would require enormous computing resources and would be significantly slower compared to actual quantum computing. It is still unknown whether quantum effects actually play a role in conscious information processing.

The view, that a person's mental activities are completely defined by the behavior of neurons, glial cells as well as the environment they reside in inside the brain, is also taken by Francis Crick, co-discoverer of the molecular structure of the DNA (Crick, 1994)). Kurzweil (2012)) also views consciousness as an emergent property of a complex physical system. This view is also shared by Minsky (1988)). Of course, this does not leave any room for free will. If quantum effects play

no role in the behavior of a person, then the behavior would be governed by classical physics alone, and hence it would be possible (at least in theory) to estimate the behavior of a person if the environment of this person could be measured with sufficient accuracy. Christof Koch teamed up with Francis Crick to search for the neural correlates of consciousness (Koch, 2004)). According to Koch, a key function of the neuronal correlates of consciousness is to sumarize the present state of affairs of the world. This summary is then made available to the planing stages of the brain. He also assumes that perception occurs in discrete processing episodes, i.e. snapshots. A stream of consciousness consists of a sequence of such snapshots. Even though finding the neural correlates of consciousness is highly important, a more abstract approach may also be beneficial. Interestingly, Koch also suggests that conscious percepts are private and cannot be directly communicated, only by way of example or comparison. Koch (2019)) argues (with reference to the integrated information theory (Tononi, 2012; Oizumi et al., 2014))) that consciousness is widespread but can't be computed. However, the integrated information theory is basically a method to locate structures that are particularly useful for information processing. In the process, a value called Φ is computed that essentially is a measure of consciousness. It tells us which structures may be relevant for generating consciousness. Unfortunately, it does not tell us how to create conscious entities.

IX. CONCLUSION

We argue that consciousness is nothing mysterious and that it can be created using computational processing. It is possible to create certain types of qualia. At least qualia like color or those during object perception. Consciousness is equivalent to the communication center perceiving (or rather processing) external or internal events. We have learned to say "I" and to explain to our peers what our body/brain is doing. According to this theory, the job of the communication center (consciousness) is (a) to analyze what the body experiences (internal and external events), (b) to keep a record of it, and (c) to explain it to our peers. We argue that these components give rise to consciousness. Given these components, we are in a position to move towards creating machine consciousness.

As we have shown above for the quale color, qualia are not arbitrary. Color is essentially a three-dimensional descriptor that describes the reflectance function of objects at any given point. Hence, color perception is comparable across individuals. We argue that the quale color is due to the mathematical structure of the space of reflectance. Given this result for color perception, we assume that the same also holds for other types of qualia. Qualia are grounded in reality due to our evolutionary history. Qualia serve a purpose. Their purpose is to help the organism to survive in its environment and to eventually reproduce. We also argue that it is possible to generate the quale color in a computationally created entity.

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