Psychological, Computational and Robotic Models of Time Perception

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Abstract

Animals exploit time to survive in the world. Temporal information is required for higher-level cognitive abilities such as planning, decision making, communication and effective cooperation. Since time is an inseparable part of cognition, there is a growing interest in artificial intelligence to time, which has a possibility of advancing the field. This study aims to provide researchers with an interdisciplinary perspective on time. Firstly, we briefly discussed the necessary information from psychology and neuroscience, such as characteristics and models of time perception and related abilities. Secondly, we investigated the emergent computational and robotic models of time perception. As a result of the review, we observed that most timing models showed a sign of dedicated time processing like the emergence of clock-like mechanism from the neural network dynamics and revealed a relationship between embodiment and time perception. We also noticed that most models of timing developed for either sensory timing, the ability of assessment of an interval, or motor timing, ability to reproduce an interval. Additionally, the number of timing models capable of retrospective timing, which is the ability to track time without paying attention, is insufficient. In this light, we discussed possible research directions to promote interdisciplinary collaboration for time perception.

Psychological, Computational and Robotic Models of Time Perception

Introduction

Time, according to Kant (Burnham, 2008), along with space, is a main parameter constituting the possibility of knowledge. Since time conveys information regarding the current and future state of the environment, biological systems can organize their functions, behaviors, and cognitive abilities according to temporal information (Mihailović, Balaž, & Kapor, 2017). It was shown that a wide range of animals is capable of time-place learning which is the ability to associate place and time for avoidance from predators, localization of resources, and therefore, gaining survival advantage (Mulder, Gerkema, & Van Der Zee, 2013). Moreover, it was found that vertebrates having smaller bodies and higher metabolic rates perceive time passing slower in comparison to ones having larger bodies and lower metabolic rates because perceiving in higher temporal resolution returns an energetic cost (Healy, McNally, Ruxton, Cooper, & Jackson, 2013). The difference in subjective time perception as a function of body size and metabolic rate affects the amount of energy saved, and accordingly, provides a survival advantage to animals (Healy et al., 2013). These findings are not surprising because we know that animals navigate not only in space but also in time in order to show robust and adaptive behaviors. Thus, it can be concluded that animals do not live in a three-dimensional world but live in a four-dimensional one, involving time.

Animals are robust and adaptive biological systems. From this perspective, according to Pfeifer, Lungarella, and Iida (2007), understanding them might be a source of inspiration for developing robust and adaptive systems to environmental changes and perturbations. In this light, embodied artificial intelligence takes inspiration from biological systems and their interactions with their environment. Studying how biological systems acquire temporal information and how they use it to scaffold sensory, motor, and cognitive processes is an essential topic for further research in embodied artificial intelligence, cognitive robotics and computational psychology.

This type of research might reveal two positive outcomes. The first outcome is the

exploitation of temporal information by artificial intelligence systems. As emphasized by Maniadakis and Trahanias (2011) and Maniadakis, Wittmann, and Trahanias (2011), the use of temporal information in artificial systems was limited, although it is necessary to develop intelligent systems that efficiently interact with their environments. For example, in human-robot interaction scenarios, intentions of agents' behaviors and their causes are not directly observable. Think about a shared work-space where a robot should collaborate with different human partners; each has a different way of working. Even though it is the very same job, some people might be in a rush because of perceived time pressure or a personality trait. The differentiation of these two requires learning fine temporal dynamics of behaviors of people. Therefore, the value of this type of knowledge is tremendous for autonomous systems. On the other hand, time perception tasks in animal and human timing can be utilized to figure out whether algorithms developed by artificial intelligence researchers can exploit temporal information and, if they can, how these algorithms achieve this ability (Deverett, Faulkner, Fortunato, Wayne, & Leibo, 2019).

The second outcome of studying how biological systems use temporal information computationally is obtaining plausible hypotheses and remarkable insights about time perception mechanisms in biological systems (Addyman, French, & Thomas, 2016; Deverett et al., 2019; N. F. Hardy & Buonomano, 2016; Maniadakis et al., 2011). Probably because of these reasons, there is a growing interest in developing computational and robotic models that can use temporal information (Addyman et al., 2016; Deverett et al., 2019; Duran & Sandamirskaya, 2017; Hourdakis & Trahanias, 2018; Koskinopoulou, Maniadakis, & Trahanias, 2018; Maniadakis & Trahanias, 2012a, 2014, 2015; Maniadakis et al., 2011; Roseboom et al., 2019). However, we could not find a review study integrating knowledge about time perception with all perspectives, including psychology, cognitive science, neuroscience and artificial intelligence, reporting recent findings in the literature and discussing possible research directions to promote interdisciplinary collaboration in the future.

This review study is composed of three sections. In the first section, we briefly

discussed necessary concepts regarding the use and processing of temporal information in natural cognitive systems (see mind map in Figure 1). In section two, we investigated computational and robotic models of time perception. We categorized these models into two groups, namely cognitive and emergent models, and limited our discussion to emergent models of time perception (see mind map in Figure 2). In the final section, we made a general discussion regarding the current status of the literature and presented a set of possible research questions.
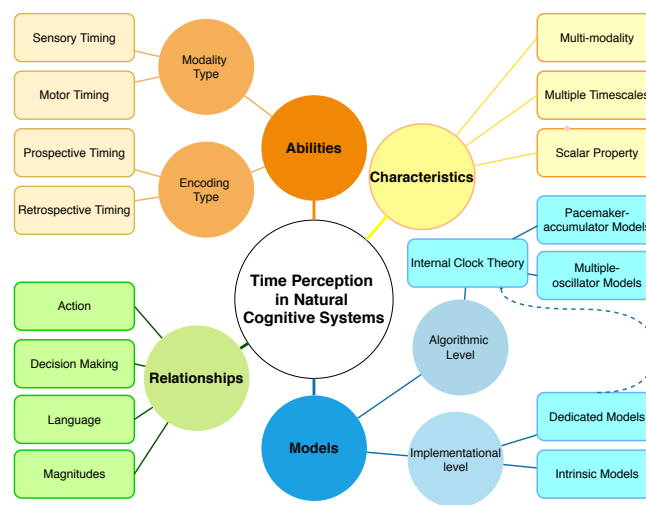

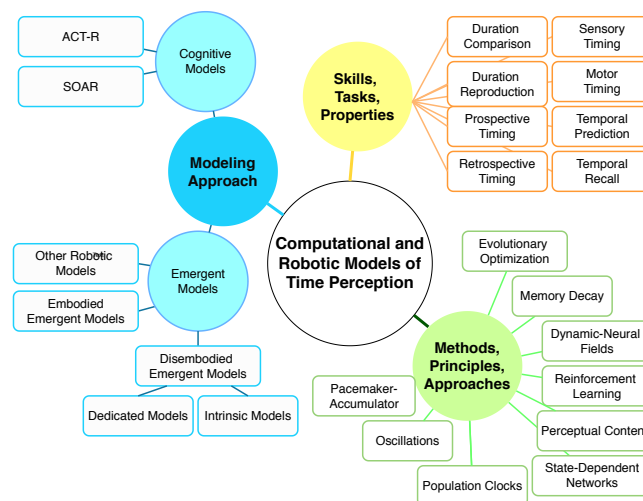*Figure 1.* A mind map for natural cognitive systems of time perception

Figure 2. A mind map for computational and robotic models of time perception

Time Perception in Natural Cognitive Systems

Here we briefly discussed the distinguishing characteristics of time perception in animals, including humans. We then elaborated classical time perception models explaining how animals use temporal information. Additionally, we emphasized the connection between time and other cognitive abilities and the maturation of time perception throughout the development. These topics will help us to refine our discussion about computational and robotic models of time perception.

Characteristics of Time Perception

Multi-modality of time perception. Time perception has several distinguishing characteristics. One characteristic of time perception is that the interaction between different sensory modalities forms subjective time perception (Bausenhart, de la Rosa, & Ulrich, 2014; Vroomen & Keetels, 2010). For example, think about a person talking on TV. Normally, mouth movements and language are out of sync; however, we perceive them as if they happen at the same time. This phenomenon is called *temporal ventriloquism* (Bausenhart et al., 2014) and shows the fact that time perception is *multi-modal*.

Timescales of time perception. Animals can use temporal information in different timescales. For this reason, time perception is investigated in at least four timescales, namely *microsecond timing*, *millisecond timing*, *second timing*, *circadian timing*, each of which contributes to different abilities in organisms' lives (Buhusi & Meck, 2005). For example, it was shown that timing up to milliseconds is crucial for successfully producing speech (Schirmer, 2004) and motor control (Sober, Sponberg, Nemenman, & Ting, 2018), on the other hand, timing between seconds to minutes is essential for working memory maintenance (Brody, Hernández, Zainos, & Romo, 2003) and the production of action sequences (Bortoletto, Cook, & Cunnington, 2011). Controlling the sleep-wake cycle and metabolism, circadian timing depends on the day-night cycle (Buhusi & Meck, 2005; Czeisler et al., 1999). The literature for each timescale is very detailed and cannot be covered in a review study. For the sake of

brevity, we restricted our discussion to milliseconds-to-seconds and seconds-to-hours.
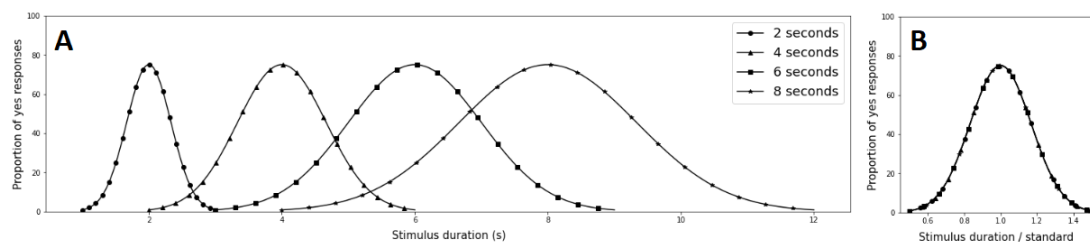
Figure 3. The figure is adapted from (J. Wearden, Denovan, & Haworth, 1997) and shows an abstract depiction of scalar property. In a *temporal generalization task*, animals receive a standard and a target stimulus and are trained to press yes when the standard stimulus is the same as the target stimulus. In the figure, different experimental groups (standard stimulus with a duration of 2, 4, 6, and 8 seconds) are given in the x-axis. (A) The maximum proportion of yes responses is converged to the real duration and the variance of the proportion of yes responses increases as the duration to be estimated increases. (B) Moreover, the increase in variance is linearly proportional to the estimated duration. This is the scalar property of time perception.

The scalar property of time perception. An interesting feature of perceptual discrimination is that it depends on the ratio between two values, which is called *Weber's law* and seen in quantity discrimination in different domains such as number, length, and duration. Weber's law reveals itself as *scalar property* in duration discrimination (see Figure 3) (Matell & Meck, 2004). The scalar property defines a strict mathematical relationship between estimations (target duration) and the interval being estimated (standard duration). It refers to the fact that as the duration to be estimated increases, the deviation of estimations from the standard duration increases *linearly.* For the scalar property, "the standard deviations of time estimates grow as a constant fraction of the mean," (Ferrara, Lejeune, & Wearden, 1997, p. 218) meaning that coefficient of variation statistic (standard deviation/mean or CV) remains constant. This property was observed in duration estimation performances of other animals such as rats and pigeons (Buhusi et al., 2009; Lejeune & Wearden, 2006; Malapani & Fairhurst, 2002). However, for very short ($<$ 100 ms) and long durations

($>$ 100 s) and challenging tasks, deviations were observed (Lejeune & Wearden, 2006). For instance, Ferrara et al. (1997) conducted a study with two conditions in which participants were to detect whether the target duration is the same as the standard duration (see 3). For the easy condition, target durations were prepared around 600 ms with 150 ms steps (150, 300, 450, *600*, 750, 900, 1050), whereas for the hard condition, they were prepared with 75 ms steps (375, 450, 525, *600*, 675, 750, 825). Surprisingly, the group in the hard condition was more sensitive to difference in two stimulus durations than the easy condition. This result was contrary to expectations of scalar property of time perception.

Despite its distinguishing characteristics, the ability to time is not isolated. In fact, it scaffolds other perceptual, motor and cognitive processes. In the next section, we will try to shed on light on the relationship between time perception and its relationship between other cognitive abilities.

Time perception and related cognitive abilities. Time has an important role in performing actions. It was found that the duration between action execution and the expected sensory input affects the sense of agency (Stetson, Cui, Montague, & Eagleman, 2006), which affects in turn the perceived duration in between (Haggard, Clark, & Kalogeras, 2002; Moore & Obhi, 2012). The former was observed in the *sensory-motor temporal calibration paradigm*, while the latter evidence was observed in the *intentional binding paradigm*. In the sensory-motor temporal recalibration paradigm, researchers put an artificial lag between a button press (action) and a beep sound (effect). After the training, the lag between the action and the effect is removed and participants start perceiving as if the effect occurred before the action (Stetson et al., 2006). An opposite effect was seen in the *intentional binding paradigm*. When people think that they are responsible for the effect, they perceive that the duration between the button pressing (action) and the beep sound (effect) is closer than they actually are (Haggard et al., 2002; Moore & Obhi, 2012). These two paradigms show that time plays a role in forming the sense of agency and connecting the action (cause) and effect into one another.

In addition to the binding of an action and its effect, time is a property that people consider in decision making (Klapproth, 2008). For example, the classical tasks shown in Figure 4A and Figure 4B require the ability to making decision by estimating time. Time is also important for decision making in real-world context, which can be seen in Figure 4E. In their seminal work, Leclerc, Schmitt, and Dube (1995) showed that people tend to decide for events whose durations are certain rather than suspicious. It is also important to note that time determines the value of outcomes. In fact, for an agent, immediate and delayed outcomes do not have the same value, which is called *temporal discounting* (Critchfield & Kollins, 2001). It is believed that this a personality trait affecting people's ability to make long-term plans (Simons, Vansteenkiste, Lens, & Lacante, 2004).
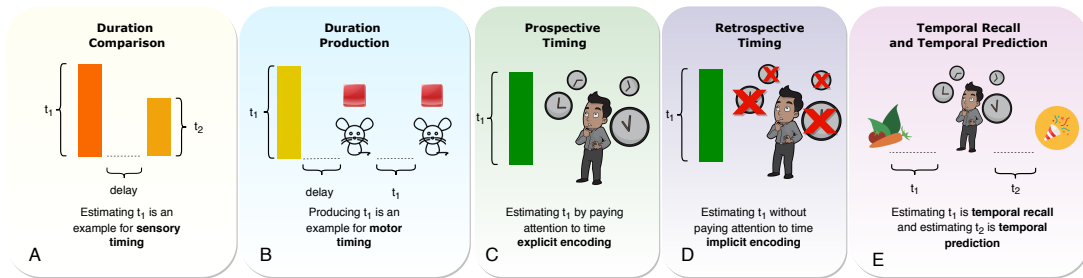
Figure 4. The figure shows interval timing abilities and related tasks. (A) In a classical duration comparison task, the agent is asked to decide which stimulus is longer or shorter (t_1 and t_2). The task requires estimating the duration of t_1 and t_2. Duration estimation for one sensory stimulus is called sensory timing. (B) In a classical duration reproduction task, an agent is given a target duration that should be produced by marking the start and the end of the event by pressing a button. Producing t_1 requires motor timing ability. (C) One can estimate the duration of an event by paying attention or (D) without knowing. E) In addition to these abilities, one can estimate when an event occurred and when an would occur.

Investigating the connection between language and time perception, J. Wearden (2008) focused on the speech control and metaphor comprehension. The former is an example of how time perception affects language understanding and use and the latter

is an example of how language affects perceiving time. The research suggested that duration discrimination problems in speech result in speech perception and production problems (Tallal, 2004); children having poor reading abilities also have poor temporal judgment capabilities (May, Williams, & Dunlap, 1988) and training for temporal discrimination improves phonetic identification (Szymaszek, Dacewicz, Urban, & Szelag, 2018). It is also claimed that language determines how we perceive time. Boroditsky (2001) observed that English people perceive time as if it flows horizontally, whereas Mandarin people thought that it flows vertically. Moreover, Hendricks and Boroditsky (2017), in an experimental study, showed that learning a new metaphor to talk about time leads people to form its non-linguistic representations.

Time perception and magnitude perception. A stimulus has measurable properties, namely magnitudes, such as its volume in space, number and duration. There is a substantial amount of research showing that magnitude perception skills are not isolated from one another. For example, Brannon, Lutz, and Cordes (2006) found that infants who are at their six months of age showed the same sensitivity to number, time, and area in a discrimination task. Xuan, Zhang, He, and Chen (2007) showed that error in temporal judgment is affected by other magnitudes such as number, size and luminance. The relationship between magnitudes leads researchers to think that there can be a common magnitude representation system in the brain. This idea was theorized by Walsh (Bueti & Walsh, 2009; Walsh, 2003) and called *a theory of magnitude (ATOM)*. According to this theory, time, space and number are sensory-motor decision variables that are used for action execution. For this reason, they are processed in a common magnitude system located in the inferior parietal cortex and this system is hardwired by the evolutionary process. ATOM proposes a map between magnitudes from birth, while other researchers suggest that this map might be established after birth. Cantlon (2012) listed possible explanations about how the mapping between different magnitudes is established. The map might be formed via statistical associations throughout the development (the longer the distance one walks, the longer the duration it passes) or in the conceptual domain through analogical

reasoning or building metaphorical relationships (Boroditsky, 2000). The map might be generated because similar intensity rates of different magnitudes are processed with the same system (a bright light activates the same representation with a loud tone) (Cantlon, 2012; Gibson, 1969) or it might be a side effect of development. According to this hypothesis, in the earlier years of infancy, infants experience synesthesia-like experience due to the abundant connections in the brain. Throughout the development, connections between magnitudes are kept while others are pruned (Maurer, Gibson, & Spector, 2013; Spector & Maurer, 2009). Another possibility would be that ability to use one magnitude might be evolved from the other, which leads the system to share the same representations and computational resources (Cantlon, 2012).

Timing is not isolated from other cognitive abilities and magnitude types. Thus, many models and theories are developed to achieve an integration (N. A. Taatgen, Van Rijn, & Anderson, 2007; Walsh, 2003). At the same time, timing is not stable or static from birth; rather, it maturates and changes throughout the development. In the next subsection, we will give a brief outline on the development of time perception.

The development of time perception. In the course of development, the timing abilities of human babies see substantive changes (McCormack, 2015). Despite these changes, in the early year of their lives, they still have remarkable skills. For example, the evidence showed that infants form a temporal predictions (Colombo & Richman, 2002) and they are sensitive to the interval between two stimuli (Brannon, Libertus, Meck, & Woldorff, 2008; Brannon, Roussel, Meck, & Woldorff, 2004). Further research revealed that the ability of infants to discriminate different durations develops during their development. It was observed that 3-month-old infants can discriminate durations with 1:3 (Gava, Valenza, Di Bono, & Tosatto, 2012), 5- to 6-month-old infants with 1:2 (VanMarle & Wynn, 2006), 10 month-old infants with 2:3 ratio (Brannon, Suanda, & Libertus, 2007) (t_1:t_2 in Figure 4A). That is, although infants can process temporal information from the birth, they maturate to distinguish more complex proportions throughout the childhood (Allman, Pelphrey, & Meck, 2012).

Up to this point, we provided a brief outline about time perception in animals. In

the following subsections, we elaborate basic timing abilities and temporal information processing models trying to explain them.

Time perception tasks and abilities. *Duration* is a feature of sensory stimulus having a start and an end. Ability to tell duration in seconds-to-hours range is considered as *interval timing* (Oprisan & Buhusi, 2014), although the term can have a broader meaning encompassing milliseconds-to-seconds range (Paton & Buonomano, 2018). Studies conducted for investigating the abilities of animals in interval timing revealed important tasks (see Figure 4).

Interval timing tasks can be grouped into two major classes according to the use of temporal information. While tasks requiring duration estimation of sensory stimuli are named as *sensory timing* tasks, tasks requiring to regenerate duration information are called as *motor timing* tasks. That is, sensory timing is about how much time is passed, while motor timing is about when or how long a behavior is shown. For motor timing, temporal information should be reproduced by motor commands (Buonomano & Laje, 2011). In Figure 4A and Figure 4B, basic tasks for sensory and motor timing are shown.

A further categorization can be made between timing tasks by concerning the type of encoding. Animals can encode temporal relationships of environmental dynamics unconsciously. This is called implicit encoding of temporal information and assessed with a *retrospective timing* task in which subjects are not informed before they are asked to estimate a duration (Block, Grondin, & Zakay, 2018; Grondin, 2010) (see Figure 4D). If subjects are explicitly informed and asked to estimate a duration, the task is a *prospective timing* task (see Figure 4C) (Block et al., 2018; Grondin, 2010). For example, if subjects are asked to guess how long the computer has been open, this is a retrospective timing task because subjects do not deliberately track the duration. Since they implicitly encode it, they should guess by counting on their memory. If subjects are asked to wait and deliberately track how long the computer will be open until it is closed, this is a prospective timing task because subjects give their attention to time.

In addition to the encoding of time, whether the estimated duration is in the past or the future is another conceptual distinction (see Figure 4E). For the past, we can

define a term called temporal recall (already named as *timing when* by Maniadakis and Trahanias (2016)), which is the ability to estimate when an event occurred. On the other hand, for the future, temporal prediction is the ability to use learned temporal dynamics to assess when an event would occur or be completed.

In the subsequent sections, We will evaluate computational and robotic models by asking whether the target model mentions explicit or implicit encoding (prospective and retrospective timing), whether the current model is capable of representing or regenerating the duration (sensory and motor timing) and whether the model shows scalar property (see Figure 4). Before reviewing these models, we will investigate temporal information processing models that aim to explain performances in human and animal timing.

Temporal Information Processing Models

Explaining how animals process temporal information is the central tenet of time perception research. In the literature, two types of models, namely *dedicated* and *intrinsic models*, are the two competing explanations (Ivry & Schlerf, 2008). As for dedicated models, specialized functions contributing to temporal information processing are localized on the same part of the brain, or different functions are localized on different parts of the brain. On the other hand, *intrinsic models* postulate that temporal information processing does not depend on specific brain regions but is a function of neural populations (Ivry & Schlerf, 2008). Dedicated and intrinsic models consider the biological basis of timing; in other words, they are in the implementational level of explanation. On the other hand, these models are influenced by an information processing model in the algorithmic level. This model is put forward by *internal clock theory* suggesting that there are specialized processes and representations for timing. Since the theory assumes specialized brain areas for timing, it has a close relationship with dedicated models of time perception (Church, 1984; Meck, 1984). In the next subsection, we will investigate the relationship between internal clock theory and dedicated models of time perception.

Internal clock theory and dedicated models.   According to the internal clock theory, a mechanism resembling a clock turns physical time to the subjective experience of time. This theory was put forward as a result of the studies conducted by Treisman (1963) in psychophysics and Gibbon et al. (Gibbon, 1977; Gibbon, Church, & Meck, 1984) in animal learning. An internal clock is formed with *clock, memory and decision phases* (Church, 1984) (see Figure 5). In the clock phase, a module named *pacemaker* generates rhythmic pulses and sends them to an *accumulator* through a *switch* determining the frequency of passing pulses. In the memory phase, rhythmic pulses generated in the clock phase are sent to the working and the reference memories. While working memory stores the current amount of pulses generated by the pacemaker, reference memory stores the earlier amount of pulses that have been learnt. In the decision phase, pulses in working memory and reference memory are compared to decide whether they correspond to the same temporal interval (Allman, Teki, Griffiths, & Meck, 2014). The internal clock theory offers an explanation about how animals learn a duration in a fixed-time interval operant conditioning procedure (Skinner, 1990), in which an animal learns to press a button at certain temporal intervals defined by researchers to receive reward. In the initial trials of the procedure, the animal starts pressing the button randomly. As the experiment unfolds, the animal stores the required pulses to press the button in reference memory and presses the button when enough pulses are accumulated. Since the amount of pulses are compared, the animal's temporal estimations obey Weber's law.
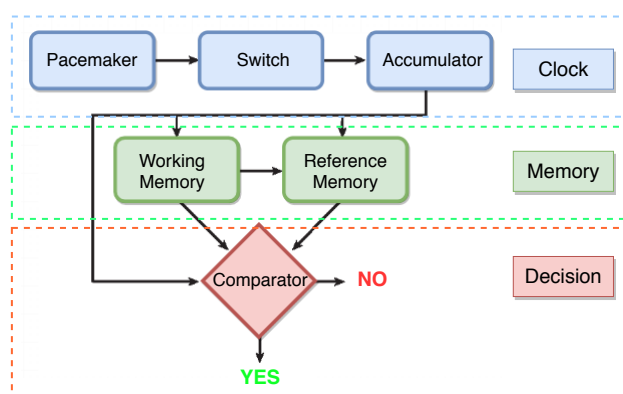

Figure 5. The information processing model of the internal clock theory

Specialized functions proposed by internal clock theory inspire dedicated models of time perception, which assume that these functions are realized in the brain. According to the *specialized timing models*, so-called internal clock is hypothesized to be located in one part of the brain, such as cerebellum (Ivry, Spencer, Zelaznik, & Diedrichsen, 2002), basal ganglion (Harrington, Haaland, & Hermanowitz, 1998), supplementary motor area (Macar, Coull, & Vidal, 2006) or right prefrontal cortex (Lewis & Miall, 2006); whereas for the *distributed timing models*, functions of internal clock are distributed in the brain (Ivry & Schlerf, 2008).

There is substantial amount of work in favor of the internal clock theory. Recall that the theory assumes a pacemaker that generates pulses and an accumulator that stores them (see Figure 5). Treisman, Faulkner, Naish, and Brogan (1990) and Treisman and Brogan (1992) found that repetitive visual and auditory stimuli can affect the frequency of pulses emitted by the pacemaker and therefore change the perceived duration as if it lasted longer. Meck (1983) showed that the pharmacological manipulations selectively change the performance of memory and decision processes in the internal clock. His work pointed out that the increased dopamine level extends the perceived duration by increasing the number of pulses emitted by the pacemaker. According to Gibbon (1992), an internal clock that shows variance in the encoding and retrieval phases can show the scalar property. Further evidence for the theory is related to a property of temporal representations. Since the internal clock is a general time-keeping mechanism, the theory assumes that temporal representations are amodal. In theory, amodal representations should pass one modality to another without notable performance differences. One evidence for this was found by Keele, Pokorny, Corcos, and Ivry (1985), who showed that the accuracy with which participants' time the same interval with a finger, foot or by observation are correlated to each other. In other words, people being successful in sensory timing were also successful at motor timing and vice versa. On the other hand, many influential work questions the amodal nature of temporal representations. For example, it was shown that auditory stimuli are experienced longer than visual stimuli, even though they have the same duration

(J. H. Wearden, Edwards, Fakhri, & Percival, 1998). It was suggested that there are different mechanisms for sensory and motor timing (Buonomano & Laje, 2011). In addition to modality-dependent temporal representations, subjective time is multi-modal (Bausenhart et al., 2014; Chen & Vroomen, 2013; Vroomen & Keetels, 2010). It must be pointed out that the internal clock is a high-level and generic cognitive mechanism. Recent research comes up with considerable challenges with this idea by selectively manipulating perceived duration of stimuli across visual space (Ayhan, Bruno, Nishida, & Johnston, 2009; Johnston, Arnold, & Nishida, 2006). This type of manipulation suggests the possibility of an inherent association between space and time and thus validates a modality-specific timing mechanism in the brain. Moreover, following this research line, Gulhan and Ayhan (2019) questioned whether a time pathway specialized for processing time as a property of visual information exists and found an evidence for the relationship between sensory processing and time perception in higher level motion areas. That is, for brief time intervals, namely milliseconds, there can be modality-dependent neural pathway for processing time, which connects early visual system to higher level cortical areas (Gulhan & Ayhan, 2019).

Apart from the possibility of modality-dependency and multi-modality of temporal representations, another limitation of the internal clock theory is that the assumed internal clock needs a reset point and can only encode the duration of the stimulus explicitly (Gibbon, 1977; Treisman, 1963). Thus, it gives a priority to the prospective estimation of time. Finally, the localization of the internal clock in the brain is still a matter of debate (for candidate brain areas, refer Allman et al. (2014)). Internal clock theory, despite its limitations, supports an intuitive mechanism that counts time.

There is another group of models trying to explain time perception without depending on a clock-like mechanism, which is intrinsic models (Ivry & Schlerf, 2008). Since they propose that neural groups can process temporal information, they are generally immune to problems that are faced by internal clock theory.

Intrinsic models.   Intrinsic models state that time perception does not depend on specialized brain regions. Theories relying on intrinsic models collaborate intensely

with neurocomputational models to investigate the underlying mechanisms of time perception; for this reason, these models will be detailed in following sections.

An intrinsic model which does not have a computational implementation is *energy readout theory* proposed by Pariyadath and Eagleman (2007) in order to explain the results of the oddball paradigm, in which subjects are presented with a sequence formed by standard and target stimuli as in Figure 3. However, in this paradigm, there are two types of target stimuli; one of which is way less frequent than the other, called oddball stimulus. Surprisingly, oddball stimulus is perceived longer than the more frequent stimulus (Tse, Intriligator, Rivest, & Cavanagh, 2004; Ulrich, Nitschke, & Rammsayer, 2006). According to *energy readout theory*, the magnitude of neural activation codes the duration of stimulus and determines whether the stimulus is perceived shorter or longer. Since predictability leads to suppressed neural activation, subjective duration of the frequent stimulus is shortened.

Intrinsic models consider neural populations as the primary actor of time perception. For this reason, they are better at explaining *modality- and task-based performance differences* in timing (Spencer, Karmarkar, & Ivry, 2009). On the other hand, these models cannot explain performance transitions between modalities and they are limited to milliseconds (Ivry & Schlerf, 2008). Intrinsic models assume that neurons held in the ordinary cognitive tasks might be used for temporal processing (Ivry & Schlerf, 2008; Karmarkar & Buonomano, 2007).

In this subsection, we provided a brief summary about time perception models trying to explain how animals process temporal information. In the next section, we will investigate the computational and robotic models of time perception.

Computational and Robotic Models of Time Perception

Investigating how animals process temporal information and mimicking the same principles by computational and robotic models enable us a chance to develop robust and adaptive systems. Also, time perception tasks that are used to study how animals perceive time can be used to evaluate the capabilities of computational agents and

understand them better. It is important to note that the relationship is not one-sided. Investigations with computational agents might reveal possible hypothesis and significant insights about how animals use temporal information in the environment.

According to Vernon, Metta, and Sandini (2007), computational models can be classified into two major classes: cognitive and emergent models. While *cognitive models* focus on the information processing and symbol manipulation to explain cognition, *emergent models* focus on the abilities that are emerged from the relationship between autonomous systems and their environment. The embodiment is not crucial for cognitive models, whereas, for emergent models, the embodiment is a must. Another explanation of emergent approach can be found in the cognitive science literature. According to McClelland et al. (2010), emergent approach is based on the idea that operations of sub-cognitive processes result in behavior and tries to model cognitive processes in the sub-symbolic level. Since we consider emergent models of time perception in this review, we accepted the definition of McClelland et al. (2010) to include neurocomputational models of time perception. For cognitive models of time perception, refer to Anamalamudi, Surampudi, and Maganti (2014) and Komosinski and Kups (2015).

In addition to emergence, embodiment is another property of computational models. We accepted that embodied models are the models forming their experience through *"sensory and bodily interaction with their environment"* (Mainzer, 2009, p. 303) and disembodied models are the models that do not focus on experience formation. Relying on this definition, we grouped emergent models as *embodied emergent models* and *disembodied emergent models*. Recall that time perception models are grouped into two classes in the literature, namely dedicated and intrinsic models. This gives us a chance to further categorize disembodied emergent models into two kinds as *disembodied emergent dedicated models* and *disembodied emergent intrinsic models*. The categorization we employed is given in Figure 6 and a summary of computational and robotic models to be considered is given in Table 1.
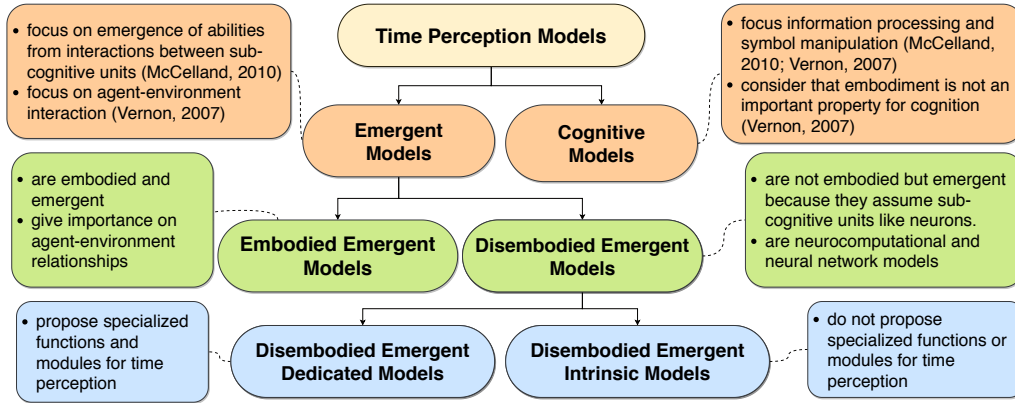
Figure 6. Embodied and disembodied models of time perception

Table 1

The Emergent Computational and Robotic Models of Time Perception

Cat	Name	Mechanism	SP	ST	MT	PT	RT	Comment
DEDM	Perception-based model (Roseboom et al., 2019)	Counting salient change	✔	✔	-	✔	-	accounts the effect of perceptual content on time estimation.
	Multiple oscillator models: BF (Miall, 1989)	Oscillations in different frequencies	✗	✔	-	✔	-	the first multiple oscillator model of time perception.
	Multiple oscillator models: SBF (Buhusi & Oprisan, 2013)	Tracking oscillations in memory	✔	✔	-	✔	-	the first perceptron-based realization of multiple-oscillator models.
	Memory decay models: GAMIT-net (Addyman & Mareschal, 2014)	Exploiting memory decay process for timing	✔	✔	-	✔	✔	shows wide range of abilities.
	Evolutionary models: Neuro-evolutionary optimization (Maniadakis & Trahanias, 2016)	Universal timing module	✗	✔	-	✔	-	the first model capable of telling when an event happened.

Table 1

The Emergent Computational and Robotic Models of Time Perception

Cat	Name	Mechanism	SP	ST	MT	PT	RT	Comment
DEIM	Synfire chain model (Haß, Blaschke, Rammsayer, & Herrmann, 2008)	Synchronous firing of chains	✔	✔	-	✔	-	considers millisecond-based interval timing.
	Positive-feedback model (Gavornik, Shuler, Loewenstein, Bear, & Shouval, 2009)	Reward modulated plasticity	-	✔	-	✔	-	does not assume a special neuron type.
	State-dependent network and population clock models (N. Hardy & Buonomano, 2018; Karmarkar & Buonomano, 2007)	State-dependent changes in neural properties	✔	✔	✔	✔	-	assume that state-dependent neural properties are exploited for temporal estimation.
EM	Memory decay models: Developmental robotics model (Addyman, French, Mareschal, & Thomas, 2011)	Exploiting memory decay process	✔	✔	-	✔	-	the first embodied model.
	Evolutionary models: Duration comparison (Maniadakis & Trahanias, 2012a)	Inverse ramping activity	-	✔	-	✔	-	a self-organizing system developed with minimal assumptions.
	Evolutionary models: Duration comparison and production (Maniadakis, Hourdakis, & Trahanias, 2014)	Clock-like mechanism counting imperfect oscillations	-	✔	✔	✔	-	the possibility of the integration between dedicated and intrinsic representations.

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	Evolutionary models: Duration comparison, production and categorization (Maniadakis & Trahanias, 2015)	Clock-like mechanism counting imperfect oscillations	-	✔	✔	✔	-	shows the possibility of the integration between dedicated and intrinsic representations.
	Deep reinforcement learning models: Feedforward agent (Deverett et al., 2019)	Autostigmergic behavior	✗	-	✔	✔	-	shows the possibility of using environment to store temporal information.
	Deep reinforcement learning models: Recurrent agent (Deverett et al., 2019)	Ramping and inverse ramping activity	-	-	✔	✔	-	shows that a reinforcement learning agent can process temporal information.
	Dynamic neural field based model (Duran & Sandamirskaya, 2017)	Accumulation of memory trace	-	-	✔	✔	-	a realization of an intrinsic model in a mobile robot.
ORM	Temporal prediction model (Hourdakis & Trahanias, 2018)	Learning temporal features of actions	-	✔		✔	-	one of the first studies in the field.
	Action learning model (Koskinopoulou et al., 2018)	Learning spatio-temporal features of actions	-	-	✔	✔	-	one of the first studies in the field.

Note: Abbreviations used in the table are as follows, Cat: Categories, DEDM: Disembodied Emergent Dedicated Models, DEIM: Disembodied, Emergent Intrinsic Models, EM: Embodied Models, ORM: Other Robotic Models, SP: Scalar Property, ST: Sensory Timing, MT: Motor Timing, PT: Prospective Timing, RT: Retrospective Timing

Disembodied Emergent Models

In this section, we will discuss disembodied and emergent models of time perception (see Figure 6). These models are *neurocomputational* and *neural network-based models.* Emergent models assuming specialized functions are considered as dedicated models, whereas those focusing on the temporal processing abilities of neurons are considered as intrinsic models.

Disembodied emergent dedicated models.   Dedicated models of time perception assume that temporal information processing depends on specialized systems or functions in the brain (Ivry & Schlerf, 2008). Two types of disembodied emergent dedicated models can be defined depending on how the internal clock transforms physical time to subjective time. These models are pacemaker-accumulator models and multiple-oscillator models. They assume different physical realizations that result in a clock-like function.

Pacemaker-accumulator models.   They are currently the most prevalent models in the literature (Addyman et al., 2016; Simen, Rivest, Ludvig, Balci, & Killeen, 2013). This model family assumes that an internal clock forms time perception. What pacemaker-accumulator models specifically assume is that a pacemaker generates pulses and an accumulator collects them. This idea was realized by cognitive architectures (Addyman et al., 2016; Pape & Urbas, 2008; N. Taatgen, Van Rijn, & Anderson, 2004; N. A. Taatgen et al., 2007) and by mathematical models (Gibbon, 1992; Killeen & Taylor, 2000) in the literature. Since the pacemaker-accumulator model and the internal clock theory share similar assumptions, the same disadvantage applies to both. As we have encountered in the literature, the number of emergent realizations of the pacemaker-accumulator model is insufficient. An emergent version of the pacemaker-accumulator model was proposed by Roseboom et al. (2019). We will discuss this model in the next subsection.

Perception-based model.   Pacemaker-accumulator models do not assume a relationship between sensory information and time perception, even though temporal information is acquired through sensory modalities. Roseboom et al. (2019) proposed

an interesting idea that counting salient *visual change* is the primary mechanism of time perception. To test this idea, they adopted a transfer learning approach by using a deep image classifier, namely ImageNet (Krizhevsky, Sutskever, & Hinton, 2012). To find the salient change, they calculated the Euclidian distance between activation values of layers formed for each frame per video and accumulated a salient change if the distance exceeds a dynamically set threshold. Then, they turned accumulated changes into subjective time estimation via regression. If the change calculated from the successive activations of ImageNet is seen as a pace generated by a pacemaker, this model can be considered as an emergent realization of the pacemaker-accumulator model. Roseboom et al. (2019) observed that the model showed good performance in duration estimation. Moreover, the performance increased more when they fed the network only with screen locations that people look at. The model is capable of prospective sensory timing and mimicking the scalar property but does not address retrospective timing and motor timing abilities. Humans can track time *without sensory information*; however, the model depends on visual information. Recently, Fountas et al. (2020) extended the model proposed by Roseboom et al. (2019) and developed an integrative model of episodic memory and time perception to capture the effects of attention, cognitive load and scene type on time perception. To do this, they integrated semantic and episodic memory with time perception in *a predictive processing model* that was composed of bottom-up and top-down processes. However, the model is not emergent as it uses hierarchical Bayesian modeling to estimate salient changes and exploits experimental data for parameter fitting.

Multiple-oscillator models.   They assume that functions of the internal clock are realized by the oscillatory areas emitting oscillations in different frequencies in the brain (Matell & Meck, 2004). These models are categorized into two kinds as *Beat Frequency (BF)* and *Striatal Beat Frequency (SBF)* models (Buhusi & Oprisan, 2013; Matell & Meck, 2004; Miall, 1989). The BF model, developed by Miall (1989), assumes more than one oscillator, each of which oscillates in different frequencies and resets into the same level when a new stimulus arrives. Phases of oscillators estimate the duration

of the stimulus. However, the BF fails to satisfy the scalar property. To represent the scalar property in a oscillator model, Buhusi and Oprisan (2013) developed the SBF model to explain how mice learn a specific duration in a fixed-time interval schedule. The model is a perceptron formed with input neurons called oscillation and output neurons called memory. Oscillatory neurons oscillate and send activation to memory neurons in each trial. A trial is either a reinforced or a normal trial as in the conditioning schedule and a reinforced trial is a trial when reward is received. When the current activation is the same as in reinforced trials, memory neurons are activated. Therefore, the system learns when the reward comes from its activation. They showed that the scalar property is introduced by applying noise to the parameters of the model. Moreover, Buhusi and Oprisan (2013) simulated the effects of dopaminergic and cholinergic drugs on interval timing, which was suggested by Meck (1983). Like other models inspired by the internal clock theory, the SBF cannot explain retrospective timing because oscillators need a predefined starting point.

Memory decay models.   They hold the view that interval timing ability is grounded on memory decay processes. *Memory decay* was put forward to explain how forgetting occurs. According to the decay theory, as the time passes, the information in the short term memory fades away and, as a result, forgetting occurs. Addyman and Mareschal (2014) developed an interval timing model called GAMIT-net based on the memory decay. It is a recurrent neural network (RNN) model that receives a Gaussian distribution simulating memory decay processes as input and estimates time. GAMIT-net was trained for retrospective and prospective timing. For retrospective timing, the model was trained on the starting and ending points of each event, whereas for prospective timing, it was trained occasionally to simulate paying attention to time. As a result, Addyman and Mareschal (2014) observed that the model captures the prospective and retrospective timing performances, mimics the scalar property because of the noisy nature of the simulated memory decay and shows the effects of working memory load and attention on interval timing. Despite all of the advantages and explanatory capabilities of GAMIT-net, however, it is not clear whether the memory

decay process is the responsible mechanism of forgetting (Lewandowsky, Oberauer, & Brown, 2009).

Disembodied emergent intrinsic models.   They are disembodied emergent models accepting that neurons can process temporal information without a specialized brain mechanism. They explain how neuron groups process temporal information and might suppose special neuron types for temporal information processing. They seem to be limited to the millisecond scale (10 and 100 ms) (Block & Gruber, 2014; Ivry & Schlerf, 2008; Paton & Buonomano, 2018).

Synfire chain model.   The model, assuming special neuron types, developed by Haß et al. (2008), who prooosed that neuron groups that are organized as chains fire synchronously to represent temporal information. Each chain is composed of neurons sending activation from one another. The varying lengths of chains determine the temporal estimation error of the chain. According to the model, the representation of time is achieved via combining temporal estimations of different chains. The model can track time prospectively and shows the scalar property due to the cumulative error in the combinatio of temporal estimations. Although the model was not developed for motor timing, it is extendable. The model is not capable of retrospective timing because chains forming the model needs a starting point to track time.

Positive-feedback model.   The model tries to explain how mice learn a specific duration in a fixed-time interval schedule by exploiting the correlation between the visual stimuli that occurs when they receive reward and the duration passed (Gavornik et al., 2009). This correlation is learned with a mechanism that involves recurrently connected neurons that can show *reward-dependent plasticity*. After the training, the model shows sustained activity until the reward received. The model is based on prospective sensory timing and not capable of retrospective timing.

State-dependent network and population clock models.   These models assume that temporal information processing is a result of recurrently connected neural populations. While the state-dependent network model was developed for sensory timing (Karmarkar & Buonomano, 2007), the population clock model was developed for

motor timing abilities (Buonomano & Laje, 2011). According to the state-dependent network model, neural populations code temporal information via their *synaptic, cellular, and structural properties*. Event-related stimuli lead to *short-term plasticity*; in other words, change in the hidden state of the neural population and activation patterns (N. F. Hardy & Buonomano, 2016). The change in the state of the neural population can be used to detect the duration of an event. The model transforms temporal information to spatial with the help of short-term plasticity (Karmarkar & Buonomano, 2007). To illustrate the process, imagine skipping a stone where each bounce leads to a change in the water, as a result, patterns in the water can be used to detect a property of the stone. There are several studies that were conducted to examine the explanatory capabilities of state-dependent network models in interval timing (Buonomano & Maass, 2009; Buonomano & Merzenich, 1995; N. Hardy & Buonomano, 2018; Pérez & Merchant, 2018). In their seminal work, Karmarkar and Buonomano (2007) developed a neurocomputational model, which was composed of recurrently connected 400 excitatory and 100 inhibitory neurons. Each neuron can show short-term synaptic plasticity and inhibitory postsynaptic potential. In their simulation, Karmarkar and Buonomano (2007) visualized dynamics of two networks, one of which received one auditory stimulus and the other received two auditory stimuli 100 ms apart. They observed that networks' dynamics differ in such a way that they encode the stimulus history. Since the temporal information is converted to spatial information, it is easier to receive the stimulus history by a read-out neuron.

According to the population clock model, two systems work hand in hand to process temporal information. One of which is the population clock composed of neurons showing activation patterns as a result of the incoming stimulus; the second is the read-out neuron reading activation patterns of neurons. If a motor command is activated in a given time, neural activations in the population clock for that time point should be higher. N. Hardy and Buonomano (2018) developed a neurocomputational model to test whether sequential activation of neurons can encode temporal information for motor patterns. To achieve this, they trained an RNN that has excitatory and

inhibitory connections between neurons for generating a 5-sec target trajectory and receiving a 50 ms input as a trigger. It turned out that RNN successfully produced the given trajectory and its temporal decisions obey Weber's law (N. Hardy & Buonomano, 2018). Both state-dependent and population clock models had an ability to time prospectively, but it seems that they cannot track time retrospectively.

Up to this point, we have discussed disembodied emergent models. The capability of processing and representing temporal information emerges from the dynamics of intrinsic models; however, these models are not embodied because, in the simplest case, they do not consider an agent that receives sensory information and takes action. In the next subsection, we will cover embodied emergent models of time perception.

Embodied Emergent Models

We have not yet mentioned the relationship between being embodied and capable of perceiving time, even though the literature shows that there is a strong relationship between embodiment and temporal experience. For example, recent research showed that bodily and emotional states affect time perception (Wittmann, 2013). Moreover, some researchers consider that temporal representation is formed via bodily and emotional states (Craig & Craig, 2009; Di Lernia et al., 2018). For Craig and Craig (2009), the posterior side of the insular cortex integrates bodily states and motivational factors to form temporal representations. A study conducted by Addyman et al. (2017) showed that interval timing depends on the development of the motor system and it is believed that the supplementary motor area has a specialized place in forming the relationship between behavior and temporal representations (Coull, Vidal, & Burle, 2016; Merchant & Yarrow, 2016). Overall, accumulated research points out that the embodiment is important for time perception (for a general examination regarding the relationship between temporal cognition and embodied cognition, see Kranjec and Chatterjee (2010)). In this section, we will explain the embodied emergent models of time perception.

In the literature, there are four approaches studying time perception from an

embodied perspective, namely an approach based on *memory decay processes* suggested by Addyman et al. (2011), *evolutionary optimization* proposed by Maniadakis, Trahanias, and Tani (2009), Maniadakis et al. (2011) and Maniadakis and Trahanias (2012a, 2015, 2016), *deep reinforcement learning* introduced by Deverett et al. (2019) and *Dynamic-Neural Fields* offered by Duran and Sandamirskaya (2017).

Memory decay models.   Addyman et al. (2011) developed the first embodied model in order to explain the emergence of interval timing ability in development. The model assumes that memory decay can be turned into duration information with the help of sensory-motor processes. For example, a baby trying to reach a toy has a memory of toy decaying over time, and at the same time, reaching behavior. Throughout the development, the duration of motor behavior and memory decay are associated and the association is re-used for interval timing. Addyman et al. (2011) tested this hypothesis with an RNN model. The input was simulated via visual and auditory information derived from a Gaussian's distribution and the output was one-hot encoded arm movement. The model is a prospective sensory timing model and shows the scalar property. The model cannot explain retrospective timing and does not aim for modeling motor timing; however, it is shown in a later study (Addyman & Mareschal, 2014) that the memory decay process is expandable to retrospective timing. The model receives action information as one-hot encoded vectors and sensory information as fading Gaussian distribution. These simulation-based decisions might make it difficult to generalize the model's findings to real life. As is mentioned earlier, it is not clear whether the memory decay process is the responsible mechanism of forgetting (Lewandowsky et al., 2009). It is important to note that the model, in principle, builds a map between distance (or length) and duration based on action performed, which might relate this model to hypotheses trying to explain the relationship between magnitudes.

The model developed by Addyman et al. (2011) had strong theoretical priors and was modeled with simple simulation-based decisions to test their assumption about the role of memory-decay processes in forming interval timing. On the other hand,

Maniadakis et al. (Maniadakis et al., 2014; Maniadakis & Trahanias, 2012a, 2015) suggested evolutionary optimization as a method to develop models that have little or no assumption in order to investigate possible time perception mechanisms.

Evolutionary models. Maniadakis et al. (Maniadakis et al., 2014; Maniadakis & Trahanias, 2012a) developed a *continuous-time recurrent neural network (CTRNN)* for sensory and motor timing using an evolutionary optimization procedure. In these studies (Maniadakis et al., 2014; Maniadakis & Trahanias, 2012a), a mobile robot having a distance sensor for navigation, light sensor for passing one task to another, and a sound sensor for detecting the stimulus was used. Simulation environments used in these studies include a long corridor and agents in use had three layers receiving the sensory observation and generating motor output. While Maniadakis and Trahanias (2012a) trained the model only with a sensory timing task, namely *duration comparison*, Maniadakis et al. (2014) extended the same idea to motor timing task, namely *duration reproduction* (refer Figure 4). For duration comparison, the mobile robot had to decide which stimulus is longer than the other by turning left or right at the end of the corridor. For duration reproduction, the mobile robot had to continue its movement for the duration of the stimulus given. In the first study, Maniadakis et al. Maniadakis and Trahanias (2012a) trained the model for only duration comparison and observed that neural activation patterns show inverse ramping activity to decide which stimulus is longer than the other. Moreover, they observed that the developed system is not similar to a clock (Gibbon, 1977; Gibbon et al., 1984; Treisman, 1963).

In a further study, Maniadakis et al. (Maniadakis et al., 2014) trained the network for also duration reproduction and observed that, in comparison to the earlier study (Maniadakis & Trahanias, 2012a), neurons showed imperfect oscillatory activations that are counted by a clock-like mechanism and ramping activity. The oscillatory activity in the network confirms the assumptions of multiple-oscillator models. Maniadakis et al. (2014) also investigated the relationship between embodiment and time perception. They observed from the neural dynamics that neurons responsible for action execution were also used for interval timing. The model developed by (Maniadakis et al., 2014;

Maniadakis & Trahanias, 2012a) is successful at prospective sensory timing and models of Maniadakis et al. (2014) are successful at prospective motor timing. Researchers (Maniadakis et al., 2014; Maniadakis & Trahanias, 2012a) did not share whether the model's decisions obey Weber's law and do not aim for retrospective timing. A recent study conducted by Maniadakis and Trahanias (2015) added *past characterization* skill to the model. It is the ability to decide whether an event occurs in the near or the distant past. Since both abilities relate to the past and, therefore, memory processes, past characterization shares similarities with retrospective timing. After training the model, Maniadakis and Trahanias (2015) concluded that the network exploited a clock-like mechanism counting oscillatory activations and exploiting amplitudes of oscillatory activations as a temporal information source. This is contrary to assumptions of the pacemaker-accumulator models and internal clock theory which assumed that a pace corresponds to one static temporal unit (Gibbon et al., 1984). The clock developed by the system had a *count-up mechanism* that works during counting the duration and a *count-down mechanism* that works during the reproduction of the duration. Moreover, neurons used for ordinary tasks were also used for representing time. Since the model shows properties of both intrinsic and dedicated models of time perception, they concluded that both models might be realized in artificial brains.

Maniadakis and Trahanias (2016) took one step further by developing a model that can assess when an event occurred, which differs from the abilities that require duration estimation of a presented stimulus. While the former is an ability of *long-term interval timing*, the latter is considered as *short-term interval timing*. To model both short- and long-term interval timing in the same system, they developed a disembodied model that can tell *how long* an event took place and *when* an event occurred by adopting an incremental neuro-evolutionary optimization approach, involving two phases. In the first training phase, they trained the model to assess how long an event took place, whereas in the second, when an event occurred. The system received oscillations in four different frequencies as input, conforming with the assumptions of the SBF model (Buhusi & Oprisan, 2013) (recall that SBF is a multiple-oscillator

model). Receiving the oscillatory signals, a universal time source generated a composite time representation that was later sent to *working memory* module, which also received a static signal representing that event continues and an event id identifying events. As a result of the first training phase, the system yielded the estimated time of six events. In the second phase, Maniadakis and Trahanias (2016) trained the model for tracking when an event occurred by feeding it with the time interval between the occurrence of the event and the current time. The model developed in the first phase was a prospective sensory timing model that can track time for more than one event, which is an improvement over for interval timing models. However, the model does not show the scalar property. When it comes to the second phase, the model can be considered a retrospective sensory timing model that can continuously track the passage of time and store temporal information for different events. Maniadakis and Trahanias (2016) do not aim to capture the relationship between the perceptual content and time perception. However, it is widely accepted that time perception is multi-modal (Bausenhart et al., 2014; Vroomen & Keetels, 2010) and affected by perceptual content (Roseboom et al., 2019). The use of an universal timing module supports two approaches to mechanisms of time perception, one of which is the amodality of temporal representations and the second is the validity of dedicated models of time perception.

Since evolutionary optimization provides an opportunity to develop models with little or no assumption, it is an unbiased way of exploring possible time perception mechanisms. In addition to the use evolutionary optimization as an unbiased estimate of time perception mechanisms, reinforcement learning can be used to model agents in an end-to-end manner to get insight about possible time perception mechanisms. Recently, Petter, Gershman, and Meck (2018) proposed integration between reinforcement learning and interval timing by showing their similarities. In the next subsection, we will review a recent study (Deverett et al., 2019) investigating interval timing in reinforcement learning agents.

Deep reinforcement learning based models.   Deverett et al. (2019) investigated interval timing in *deep reinforcement learning.* They used a duration

reproduction task similar to the task employed by Maniadakis et al. (2014) (see Figure 4). The agent was an eye gaze receiving reward by moving on a two-dimensional environment, which had cues that appear to inform the agent about the current phase of the trial. In each trial, the gaze of the agent was fixated on the center of the screen and the GO cue appeared. After a small delay, the READY cue appeared and the interval to be produced by the agent was given. Then, the SET cue appeared and the agent was expected to reproduce the interval by reaching the GO location. The agent was based on A3C (Asynchronous Advantage Actor-Critic) (Mnih et al., 2016). It was composed of ResNet architecture (He, Zhang, Ren, & Sun, 2016) coupled with a multi-layer perceptron receiving the current frame of the environment, a controller network receiving input from ResNet, and policy and value networks connected to the controller. By using two types of controllers, two types of agents were generated. Each agent had either a feed-forward neural network (feed-forward agent) or a long-short term memory (LSTM) network (recurrent agent). After training, surprisingly, each agent learned the task, although the feed-forward agent learned slower and had poorer generalization. Deverett et al. (2019) investigated the hidden layer of LSTM of the recurrent agent with principal component analysis (PCA). They found that it shows an accumulating pattern until the duration reproduction phase starts and a reducing pattern while the model produces the interval. This activation is similar to the count-up and count-down mechanism observed by Maniadakis and Trahanias (2015) and Duran and Sandamirskaya (2017). On the other hand, the feed-forward agent's activations did not show a systematic pattern. To reveal how the agent solves the task, researchers investigated behaviors of the agent while solving the task and observed that the agent developed a *autostigmergic behavior* to use the environment as a temporal information source.

Deverett et al. (2019) showed the importance of recurrent information processing for developing a clock-like mechanism in the brain and a possible behavioral strategy that can be used to count time. From the coupling of environment and agent, the system can generate a memory-like mechanism that works like a clock. Whether

feed-forward agents trained by evolutionary optimization for the same duration

reproduction task show a similar autostigmergic behavior observed by Deverett et al.

(2019) is an attractive question. Models of Deverett et al. (2019) are capable of

prospective motor timing and the feed-forward model's temporal estimations seem to

obey scalar property. We think that the same reinforcement learning algorithm can be

applied to other timing tasks.

Dynamic neural field (DNF) based model.   DNF is a mathematical

formulation about how neural populations work. Assuming the principles of DNF,

Duran and Sandamirskaya (2017) developed a model that can learn and represent the

duration of action and tested their model in a mobile robot. The mobile robot should

navigate between locations while avoiding objects in a two-dimensional environment.

The model was based on elementary behaviors that represent the relationship between

neural states and actions. Each elementary behavior had three DNFs, namely intention

DNF, condition of satisfaction DNF (CoS) and condition of dissatisfaction DNF (CoD).

While intention DNF signifies the beginning of an action and sets attractors for

sensory-motor dynamics, CoS checks whether the action is completed and CoD checks

whether the current behavior is aborted if the goal could not be achieved. These DNFs

were connected to each other with a node called t that regulates the competition

between CoS and CoD. In the earlier trials of training, t gives an advantage to CoS

because the duration of action is unknown, whereas in the later trials, t gives an

advantage to CoD because action (therefore temporal dynamics of action) is learned.

Researchers showed that the model could represent, store, and update temporal

information. Also, it could detect anomalies by checking unusual differences in time.

The model learned the duration of action by accumulating new memories; consistent

memories control the behavior of the agent, whereas inconsistent memories did not.

According to Duran and Sandamirskaya (2017), the model instantiates a

state-dependent network because how time is represented is dependent on the current

situation of the network, namely the accumulation principles of the memory trace. As

with the majority of models discussed in this section (Deverett et al., 2019; Maniadakis

& Trahanias, 2015, 2016), the model showed a ramping activity. It is important to note that the model shows the possibility of the realization of intrinsic models of time perception in robots in order to extend their capabilities from milliseconds to seconds.

Other robotic models.   In this section, we examined the models mentioned in Figure 6. There are other robotic models that do not conform our categorization. Since they are one of prominent studies in robotic timing, we included in this review. For learning the temporal dynamics of actions, Hourdakis and Trahanias Hourdakis and Trahanias (2018) developed a computational model, which composed of two components, namely task progress and control. The former is responsible for detecting how much of a given task is completed, whereas the latter tracks the time of primitive motions of the action. On the other hand, for learning both spatial and temporal dynamics of an action, Koskinopoulou et al. (2018) extended the learning from demonstration (LfD) framework, which is usually used to teach robots spatial information of actions, to include temporal information. This extends model's capabilities to executing action at variable speeds and forming temporal plans.

Discussion and Conclusion

The importance of temporal cognition for artificial systems having higher-level cognitive abilities has been mentioned in the literature (Kranjec & Chatterjee, 2010; Maniadakis & Trahanias, 2011, 2012b; Maniadakis et al., 2011; Ziemke, 2003). In this review study, we presented time perception abilities in natural and artificial cognitive systems.

One of the most important discussions in the literature is whether time is processed and represented by intrinsic or dedicated systems. Considering the embodied models of time perception, we could list several mechanisms: oscillatory activations that are counted by a clock-like mechanism (Maniadakis et al., 2014; Maniadakis & Trahanias, 2015) and ramping activity in neural activations (Deverett et al., 2019; Duran & Sandamirskaya, 2017; Maniadakis et al., 2014). It seems that embodied models tend to validate dedicated models of time perception proposing an internal clock

tracking time. However, the clock proposed in these models deviates from the original dedicated models. For example, Maniadakis and Trahanias (2012a) and Maniadakis and Trahanias (2015) reported a dynamic temporal pace that is simulated by oscillatory activations. Deverett et al. (2019) observed a clock-like activation after PCA, which shows the possibility of a distributed version of dedicated models. On the other hand, using a universal time source module to develop agents, as done by Maniadakis and Trahanias (2016), that show a wide range of temporal abilities might be a way to assess dedicated representations of time. The use of a universal time source also implies that temporal representations are amodal. Overall, this review demonstrates that developing artificial agents perceiving time reveals insights to understand how time is represented and processed in natural cognitive systems.

It is generally accepted that intrinsic models of time perception are limited to millisecond range (Ivry & Schlerf, 2008). Being an intrinsic model of time perception, state-dependent networks face with the same challenge. Duran and Sandamirskaya (2017) realized a model conforming the principles of state-dependent networks in a robot that could track time successfully. We think that embodiment can be used to extend the capabilities of intrinsic models. It is also important to note that time perception cannot be easily achieved by expanding the capabilities of intrinsic models to seconds. As we have discussed, time perception has at least four timescales, namely circadian, second, millisecond and microsecond timing (Buhusi & Meck, 2005). Considering the role of time in forming experiences, we can add hours, days, weeks, months and years to this list. Furthermore, we can double the list by considering the past and the future, which surely will make the problem more complicated. Developing artificial systems that perceive the past and the present requires combining time perception with other cognitive mechanisms like working memory, as in (Maniadakis & Trahanias, 2016), long-term memory and attention.

In addition to the importance of multiple time-scales in cognitive life, it can be seen from the Table 1 that retrospective timing, learning temporal features of the environment implicitly, is largely unexplored by emergent and embodied models. In

addition to retrospective timing, how people learn complex temporal dynamics of action sequences is not discovered scientifically by computational models, although there exist robotic models developed for practical aspects (Hourdakis & Trahanias, 2018; Koskinopoulou et al., 2018).

It is necessary to note that temporal abilities that are discussed in this review are highly limited and only represent a small proportion of the field. For example, we did not include the verbal estimation of time (Block et al., 2018) and processing temporal information of sequences (N. F. Hardy & Buonomano, 2016), partly because of the sparsity of emergent models in these aspects. We also could not spare enough time to discuss more cognitive-related abilities such as mental time travel, reasoning about the future and time-dependent organizations of memory. It is exciting that further studies can investigate new abilities in artificial systems and gain insights about how natural systems can solve these problems. It is important to note that some artificial agents investigated in this review is unifunctional. For instance, the models developed by Roseboom et al. (2019), Addyman et al. (2011), and Maniadakis and Trahanias (2016) are capable of sensory timing, whereas the models developed by Deverett et al. (2019) and Duran and Sandamirskaya (2017) are capable of motor timing. It is highly probable that similar algorithms can be extended to accomplish a wider range of time perception tasks and abilities to get insights about time perception mechanisms.

In their inspirational work, in comparison to the majority of models we investigated, Roseboom et al. (2019) suggested that tracking salient change in the perceptual content might be a mechanism of interval timing and reported that it is indeed possible to ground interval timing on sensory information. Whether the very same idea can be extended to robotic agents that will operate in the real world is an appealing question to discuss.

Being essential part of cognitive life, perceiving other magnitudes relates to the perception of time. Perhaps, artificial agents that are trained incrementally or holistically for using different magnitudes can be assessed for possible overlapping mechanisms to understand the relationship between magnitudes in the brain. The

evolutionary optimization approach proposed by (Maniadakis et al., 2014; Maniadakis & Trahanias, 2012a) can be used for a minimally-biased exploration. On the other hand, ATOM (Walsh, 2003) can be evaluated in an embodied system. It is also possible that one can build a bridge between sensory-motor decision variables (Walsh, 2003) and the use of space to estimate intervals based on decaying memory trace over time (Addyman et al., 2011, 2017). This might connect time, space, and number based on actions resulting in embodied timing models capable of using magnitudes for action selection and control.

The scalar property shows exciting challenges to computational and robotic models of time perception. It is a mathematical property that temporal estimations of animals share (Buhusi & Meck, 2005; Ferrara et al., 1997; Lejeune & Wearden, 2006; Malapani & Fairhurst, 2002; Matell & Meck, 2004; J. Wearden et al., 1997). However, from an application point of view, as long as temporal estimations are accurate enough, considering the scalar property in artificial systems might not be necessary. On the other hand, from a scientific point of view, considering the scalar property in artificial systems makes it easier to generalize results to biological systems as an insight.

In this study, we discussed time perception through the lens of a wide range of disciplines. Considering the role of time in natural cognitive systems, we consider time perception as a present challenge to be met by artificial intelligence and a possible way to develop robust and adaptive systems. We also believe that developing computational and robotic systems reveal significant insights into how biological time perception emerges.

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