Society of Mind cognitive agent architecture applied to drivers adapting in a traffic context.

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Abstract
This paper challenges the idea of creating an architectural approach for designing a complex hybrid cognitive agent, i.e. an agent which possesses all reactive, deliberative and affective capabilities, outside the hierarchical paradigm. Thus, it presents an agent architecture based on Marvin Minsky’s “Society of Mind” (SoM) metaphor on human mind and cognition and shows how SoM agents, through the features implicitly generated by their design, allow a tremendous power of representation of human heterogeneity and variety of behaviours. In order to show that, the SoM general architecture is instantiated and evaluated in a cognitively demanding environment: as a driver agent in a traffic behaviour context.

Keywords
Hybrid cognitive agent, society of mind, competing agencies, driver agent, traffic behaviour

Introduction
Agents are used nowadays in more and more fields of activity, and paradigms such as agent based system, agent based modelling and simulation, agent architecture became virtually indispensable tools for solving various problems which involve adaptation and behavioural heterogeneity. However, this problem-oriented approach also generated an important drawback of agent paradigm, that is, agents are usually designed to solve specific problems. They are from this point of view unique and cannot be easily ported to other problems or fields of activity without significant alteration of the original architecture or design.

Formal classification of agent architectures exists and any newly proposed agent design is referred to as “based on” or as “belonging” to one of the formal architectural approaches. However, existing architectures are not universally instantiable for any problem; rather, each of them covers a certain part of the whole complex human cognitive capabilities and can be used in a limited range of applications. Agents were categorised over time in numerous classes and types (Caballero & Botia, 2012; Russell & Norvig, 1995), the fundamental architectural approaches from a cognitive perspective being reactive, rational and affective agents. Reactive agents can actuate simple response – usually in physical domain such as adaptation of position, velocity, orientation etc. – to local and most of the time primary stimuli such as vision, tactile perception etc., whereas rational and affective agents possess an internal representation of the environment and are able to generate action plans and intentions based on either rational or affective decision making processes respectively. Since each approach is concerned with a different set of cognitive-behavioural capabilities resultant agent designs are also limited to solving the corresponding set of problems.

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Efforts to combine architectures into hybrid designs for covering a wider range of human cognitive-behavioural capabilities exist and they consider hierarchically layered designs with reactive parts at lower levels of cognitive capabilities being commanded by rational and/or affective parts situated towards the higher cognitive levels. However, these designs proved to become rapidly logically and computationally complex when the range of cognitive capabilities widens, fact that limits their usability (Caballero & Botia, 2012).

This study proposes an alternate architectural approach for designing complex cognitive agents, i.e. agents with all reactive, deliberative and affective capabilities, outside the hierarchical paradigm. The core of a non-hierarchical view on agents stays in that reactive, deliberative and affective components may coexist at the same level in the cognitive capabilities pyramid, except they are active in different environmental contexts. They participate in the over-all decision-making process by trying to impose their own decision in a given situation; in other words their importance rises and falls according to instantaneous context the agent faces at a certain moment in time. This approach was introduced by Marvin Minsky in “Society of Mind” view on human mind and cognition (Minsky, 1985). In Minsky’s approach human mind is not a singular entity organised in a fixed hierarchical construction of cognitive capabilities but rather an entire system of competing agencies which creates a dynamic, permanently evolving society-like edifice. Such a view, arguably, describes the human nature in a more comprehensive manner than conventional hierarchical approaches. Hence an agent architecture starting from this idea would potentially offer a better representation of the variety of cognitive capabilities with a simpler and less computationally complex architectural design.

Thus the paper presents an SoM agent architecture and shows how SoM agents can successfully model human innate behavioural diversity as well as real-time adaptation. In order to show that, the agent architecture is evaluated in a cognitively demanding environment: the road traffic. An SoM driver agent is placed in various road traffic situations while the internal dynamics of its “mind” and the actuation of its decisions are assessed.

**Related work on cognitive agents**

Agents have been defined in many ways over the years and have been categorised in many formal taxonomies. From a taxonomic point of view thorough reviews of agent paradigm can be found in (Russell & Norvig, 1995; Salamon, 2011). However, from a definition point of view most definitions place agents in a perception-action cycle, shown in Figure 1, in which individual agents perceive surrounding environment through sensors and based on that generate the appropriate behaviour.

Of the many agent taxonomies two are of major concern for this study: the perception-action cycle and the cognitive capability architectural categorisation. The former is concerned with what major steps the agent takes within the perception-action cycle, while the latter shows how individual agents are decomposed in component modules and how these modules interact to generate perception-action cycles.

**Perception-Action cycle**

Perhaps the fundamental formulation of perception-action cycle is the three-step SDA (Sense- Decide-Act) cycle (Wooldridge, 2002) in which data about the world are obtained through sensors (sense), processing to those data is applied for establishing what to do (decide) and then actuators are commanded to produce behaviour (act). Cycles of an SDA type involve an autonomous context-based decision making mechanism which can function based on any kind of cognitive processing abilities. Different implementations of the decisional components generated numerous variations from the standard SDA cycle, such as Boyd’s OODA (Observe-Orient- Decide-Act) loop in defence/military applications.
(Luzwick, 2000), SIDA (Sense-Interpret-Decide-Act) loop interpretation of Sense-Response cycle in research of organisational development (Haeckel, 1999) or Sense-React cycle for wireless sensor networks optimisation (Russello, Mostarda, & Dulay, 2011).

![Diagram of an agent](image)

**Figure 1 Basic view of an agent.**

Cognitive capability architectural design

**Reactive agents.** Reactive architectures concentrate on building agents capable of fast reactions to changes detected in the immediate environment. Agents have no or very simple internal representation of the environment and they are built in a behaviour-based paradigm (Russell & Norvig, 1995), providing very tight coupling between perception and action. For this reason reactive agents belong to a Sense-React cycle, autonomous decision making (intelligence) being not an intrinsic attribute, but rather the product of the interaction between agent and environment. Reactive agents are mainly based on three major designs: standard stimulus-response (or condition-action) agent systems (Milani & Poggioni, 2007), subsumption architectures (Brooks, 1991) and agent network architectures (Maes, 1991).

Tight coupling between ‘Perception’ and ‘Action’ stages in the Sense-React loop and lack of complex decision making mechanisms give reactive agents some inherent advantages. They are ideal in very dynamic and unpredictable environments and their implementation is simple leading to low computational complexity. Also without a central planning component reactive agents have a high degree of adaptability and flexibility which makes possible their usage in massive simulations. However, their simplicity also comes with inherent limitations. Since they do not possess an internal representation of the world, decision (reaction) is based on local information only; hence they need sufficient information available from the local environment. Because of this reactive agents have short-term view, without long-term planning capabilities or decision based on global environmental context.

From a cognitive perspective, reactive agents are not considered intelligent per se but rather the multi-agent systems they are part of show emergent collective intelligence. Hence, implementations of reactive agents are limited to simple robots and reactive entities – in individual setups – or to ant colonies or swarms, bird flocks etc. – in multi-agent setups.

**Rational agents.** Rational architectures, such as Believe-Desire-Intention (Rao & Georgeff, 1995) or Procedural Reasoning System (PRS) (Ingrand, Georgeff, & Rao, 1992) concentrate on long-term planning of actions, centred on sets of goals. They are capable of deciding and acting in more than just a reactive manner, based on their own reasoning and view on the surrounding world and considering a set of alternative courses of action. Environment is represented internally as an explicit symbolic model of the world, and decisions are made through logical reasoning based on pattern matching and symbolic manipulation. Given this architectural approach, rational agents fall into the SDA paradigm when looked at from perception-action perspective. The advantage of rational agents is they can cover more real-world problems through the fact decision-making mechanisms are closer to human reasoning processes.
However, they are also more computationally complex than reactive counterparts since generation of alternate plans and processing of choice requires more complex implementation and higher computational effort. Besides, they can only model rational cognitive processes and hence generate rational behaviour, with decision-making based on choice and involving certain profit functions.

**Affective agents.** In affective architectures agents have components which in connection with other internal or external components can instantiate affective states. Thus affective agents (Broekens, Koster, & Verbeek, 2007) contain explicit or implicit representations of various affective features such as desires, emotions, moods etc. Like rational agents, affective agents also fall into SDA paradigm; however internal decision-making mechanisms in the decisional stage are different, since affective agents appeared as a response to rational agents’ inability to deal with more complex cognitive contexts which were beyond the usability range of rational decision theory tools. Appearance of affective agents was the result of a shift in AI (Minsky, 2007) and cognitive science (Thagard, 2005), when researchers realised that designing complex agents without affect may not be sufficient for there were no agents without affect in nature at all (Herrera Pérez, Sánchez Escribano, & Sanz, 2012; Parisi & Petrosino, 2010; Scheutz & Logan, 2001), let alone humans.

In the case of humans Damasio’s (Damasio, 1994) theory of somatic markers showed that normal operation of human decision-making requires an emotional mechanism which regulates rational reasoning by creating biased affective “forecasts” of potential consequences of an action. Without this emotional signal the brain only uses rational reasoning, which slows down or even jeopardise the decision-making because of the many possible conflicting options to be considered. However, not only humans, but even simple organisms with no rational capabilities were found to have certain affective underpinnings which generate various behavioural patterns such as attraction, aversion etc., whereas in a general consideration any organism/agent of a certain complexity possess affective states which act in relation with the other cognitive functions and capabilities (Scheutz & Logan, 2001; Zadeh, Shouraki, & Halavati, 2006).

**Hybrid agents.** It is somehow clear from the above discussion that none of the main architectural approaches is suitable for building complex cognitive agents. The ultimate goal of such agents is to identify and replicate the mechanisms underlying human cognition and behaviour. With a tremendous variety of such mechanisms studied by various sciences or fields of activity it becomes obvious that very little can be done by trying to work on them separately. Gershenson used a number of cognitive paradigms for modelling “animats” in a virtual laboratory, in order to evaluate their suitability for studying cognition (Gershenson, 2004). He concluded that there is no best approach, since each view treats different aspects of cognition in different contexts. Hence, most of the complex cognitive agents/theories are trying to find unified representations of these mechanisms (Clark & Grush, 1999; Froese, 2012; Gärdenfors, 2000; Newell, 1990). The most notable cognitive architectures proposed over time, such as SOAR (Laird, 2012), ACT-R (Anderson, 1996), CLARION (Sun, 2002) or CoggAff (Sloman, 2008), use some or all three types of cognitive capabilities (reactive, rational, affective) as sub-components in hierarchically layered designs. Agent’s control subsystems are arranged into a hierarchy, with higher layers dealing with information at increasing levels of abstraction. Thus, reactive component is considered as representing lower level cognitive processes, and providing fast response to events without complex reasoning. This is controlled by either a rational or an affective component (or both) situated at a higher level of cognitive capabilities which contains a world model and makes decisions according to rational or affective reasoning. A problem in such architectures is how to model the interactions between hierarchical layers and the control mechanism.

Two important control frameworks have been proposed by Müller and colleagues (Fischer, Müller, & Pischel, 1995) who classify such architectures into horizontally and vertically layered. In *horizontally layered architectures* each layer has access to sensing and acting, making a potential decomposition into
subagents possible. Each layer is connected to the sensory input and action output, and so it produces suggestions as to what actions to be taken. These suggestions are “approved”, “altered” or “dismissed” by the higher hierarchical layers. A disadvantage of this approach is the informational bottleneck which can appear in central control system. In vertically layered architectures sensory input and action output are connected to the lowest layer. Hence only the lowest layer is involved in sensing and actuating while higher layers are involved in complex processing and decision making. A multi-agent decomposition becomes difficult, and in addition, architectures of this type are intolerant to layer failure.

Hierarchical aspect of layered designs is also addressed in Sloman’s study (Sloman, 2008); he discusses a dominance dimension of architectures consisting of the amount of control exercised by higher level cognitive processes on the lower levels. The more and stricter control higher levels have on lower levels, the stronger the dominance is, while in the opposite direction the dominance decreases as lower levels are allowed other types of interactions apart from the subordination ones. The idea of hierarchy and dominance also triggers a discussion about the type of control within the hierarchy. Sloman notes that higher cognitive processes could directly turn on and off various inferior processes, or they can indirectly influence their operation acting as modulators, or in the less direct type of control they can facilitate their training and/or evolution.

Existing hybrid architectures have been criticised though for several important aspects. One is the lack of methodologies for guiding the design. Existing designs are very specific, application dependent and hence difficult to be categorised or included in certain theoretical approaches. Also since fundamental sciences have not found yet a consensus regarding which cognitive processes are positioned at which abstraction level, existing architectures and the way they describe the interactions between various agencies (i.e. reactive, deliberative, affective) are not entirely supported by formal theories.

The “Society of Mind” agent architecture

Background

“Society of Mind” paradigm, proposed by Marvin Minsky (Minsky, 1985) is largely perceived as a narrative model of human mind, rather than as a cognitive theory. However, it may contain answers for the difficult task of modelling interactions between various classes of cognitive processes, in order to design complex cognitive agents. SoM is nevertheless a valuable vision on how human actions emerge from a so-called “heterarchy” of interacting and competing internal entities. Some authors disapprove the lack of scientific validation of many concepts and ideas presented in Minsky’s approach (Ginsberg, 1991; Reeke Jr, 1991; Smoliar, 1991); however they also acknowledge that any single claim made by SoM is so true and undeniable in its common sense that Minsky’s approach despite not qualifying for a theory is also virtually unarguable with scientific methods, coming rather from an extremely pertinent observation and very deep understanding of human nature and human action formation mechanisms (Dyer, 1991; Stefik & Smoliar, 1991; Thagard, 1993).

Among the many concepts and assumptions Minsky’s theory is built on two aspects are fundamental for this study: principle of non-compromise and K-line theory of memory.

Principle of non-compromise. According to Minsky human mind contains numerous agencies which compete at any moment in time for imposing their own decision about the action to be taken. Depending on instantaneous internal and external contextual factors these agencies rise and fall in terms of their strength in the competing process. This permanent conflict-like process has always a single winner, or in other words the compromise between two agencies is impossible, hence the name “principle of non-compromise”.

...
It is a view that comes in opposition to all major cognitive agent architectures in which decision is modelled through conflict resolution mechanisms implemented through certain profit or utility functions in order to generate a convenient/compromise outcome given a set of possible courses of action. Despite his view was not formally validated in AI or unified theories of cognition, the existence of internal agencies within the mind of human individuals and the ‘non-compromising’ competition between them have been intensely studied in psychological theories under the name of “dialogical self”. Dialogical self considers human mind, in a similar manner to SoM, as a collection of voices trying to be heard and impose their own way of action. According to (Lysaker & Lysaker, 2002) dysfunctions observed by psychiatric practitioners in patients with multiple personality, dissociative disorders, schizophrenia or with decision-making disabilities are generated by a “collapse of the dialogical self”, whereas (Hermans, 2002) sees this as an “organisational problem” of self, in which voices are unable to “non-compromise” and start coexisting (overlapping) in the decision-making and hence generate ambiguous or improper courses of action.

**The K-line theory of memory.** “K-line theory of memory” assumes that memory of past actions forms the knowledge base from which entities (subagents) of the agencies in the Society (of Mind) are made of.

Decision on choosing a certain course of action is based on recalling and re-composing past facts, actions, or images of the world stocked in the long term memory following exposure to various life situations (Minsky, 1985, 1991). K-line selection “re-members” only those bits of information available in the long term memory which are relevant for the situation to which individual is exposed. The core of this idea was used in some cognitive agent architectures under the name of “chunking” (Anderson, 1996; Laird, 2012), but its computational instantiations were limited to symbolic production rules such as the rule-based chunking mechanism used for long-term knowledge-base in SOAR (Laird, 2012) or the long term declarative memory included in the meta-cognitive control layer in ACT-R (Salvucci, 2006). However, decision making in both SOAR and ACT-R relies almost exclusively on recalling and selecting facts from long term knowledge base, whereas in Minsky’s approach K-line selection is viewed only as a step within the decision-making process, i.e. “re-membering” mechanism feeds multiple agents and agencies of the mind in order to support their state update and their position within the sub-agent competition process.

**The proposed SoM agent – architectural schema**

Figure 2 shows the proposed architectural framework of an SoM agent and describes its potential internal dynamics. The agent consists of a number ‘n’ of sub-agencies A (Aᵢ; i=1,n), each of them containing a set of internal entities (basic agents) e. First, an agency Aᵢ senses the environment by gathering from the larger input dataset x (xᵢ; i=1,m) only that information which is relevant for it. Then its entities interact and update their states and through that the state of the entire agency. As a result of interaction of its internal entities the agency Aᵢ is able to propose a set K-line, of actions act which are usually the result of that particular interaction of internal entities e. However not all these potential actions are relevant to the current context (the state of the environment and the state of the overall SoM agent within the environment.), hence a K-line selector chooses from the K-line, set of potential actions only that action (or subset of actions) actᵢₐ which is strictly related to the current context in order to participate in the competition with the actions proposed by other sub-agencies. Once all agencies finish their “preparation” and the K-line selector selects the candidate action for each agency, these actions participate in a bid in which, according to a certain bidding strategy, only one course of action will win and will be transferred to effectors to be actuated in the environment.
From a Perception-Action perspective the SoM agent architecture is still in a classic SDA loop, with the SoM agent sensing the environment through its agencies, deciding about a course of action and acting upon the environment through effectors. However, the internal design of decisional stage suggests an approach such as SPNA (Sense Prepare Non-compromise Act). This approach is preferred because it shows more appropriately the real dynamics within the Perception-Action cycle. Indeed, all internal processing happening inside each agency prior to competition stage reflects the way from cognitive appraisal (sensing) to a state of preparedness in which the overall SoM agent becomes aware and prepared for multiple courses of action and their effect. For this reason “prepare” stage can be considered as a first step in the decisional process. Once the agent is aware of the multiple courses of action the next stage of the decisional process starts: the competition. Following Minsky’s principle of non-compromise this stage was named “Non-compromise”. From the cognitive capabilities architectural design point of view the SoM architecture can be treated as a non-hierarchical hybrid architecture in which several competing cognitive capabilities are simultaneously considered.
Figure 3 Non-hierarchical hybrid RRA SoM architectural schema.

Figure 3 shows a proposed Reactive-Rational-Affective (RRA) non-hierarchical hybrid architecture based on the general SoM agent shown in Figure 2. Apart from the fact an RDA SoM agent is assumed to be able to cope with complex problems which combine all three types of cognitive processes, it also can reduce its capabilities when needed by inhibiting one or more of its agencies if current tasks do not involve certain cognitive processes. It can be then assumed that an agent of this type can be easily ported over various fields of activity and could mitigate the problem-dependence drawback of existing hierarchical architectures. In the same time it also offers a certain theoretical support, even if it is based on a narrative description of human mind, rather than on well-established approaches such as symbolic AI.

In addition, the approach also allows inclusion of innate individual biases and behavioural propensities, such as personality traits, which can be fed to internal agencies together with contextual data, an aspect which was not treated in other cognitive architectures except CLARION where the idea is mentioned but not supported by any implementation methodology.

Society of Mind applied in traffic behaviour – a SoM driver agent

In order to test the proposed RRA SoM architecture we instantiate it in a cognitively diverse and demanding context – road traffic behaviour. We implement an SoM driver agent which must provide support for two key aspects in modelling traffic behaviour: diversity of non-contextual behavioural propensities and real-time context-based adaptation. As shown in Figure 3, non-contextual behavioural features are assigned to individual drivers and bias their traffic behaviour, while instantaneous environmental inputs and dynamics of internal agencies account for building real-time adaptation. In
order to do so, we consider that a driver takes three types of decision standing for the three types of agencies:

- **Reactive agency**: a driver MUST take avoiding actions (full brake, lane change) in order to escape from an immediate danger, such as a collision;
- **Rational agency**: a driver takes rational decisions in order to drive safe, to avoid annoying other drivers and to obey traffic regulations;
- **Affective agency**: a driver takes decisions based on the current emotional state regardless safety, annoyance produced to other drivers, and traffic regulations.

**Implementation**

_Behavioural propensities – innate personality features._ As discussed above, one of the important aspects of the proposed RRA SoM architectural framework is the capability of handling behavioural propensities, either innate or acquired. However, acquired behavioural propensities are not covered in this study hence, only the innate behavioural features (personality) are considered for the SoM driver agent.

Implementation of personality, as the expression of innate behavioural propensities, is based on Goldberg’s (Goldberg, 1990) five factor dimensional model of personality. The five bipolar personality factors assumed by Goldberg’s model – Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism – are represented as a 5-dimensional tuple \( P(P_O, P_C, P_E, P_A, P_N) \) with \( P_i \in (-\infty; \infty) \), where \( P_i \) are the personality factors. In order to obtain a computational representation, values of personality factors \( P_i \) are limited to the finite real interval \( P_i \in [-P_{max}, P_{max}] \), where \( P_{max} = 1 \).

Values of personality traits are considered system constants and are assigned to agent at the beginning of simulation. They are fed to internal agencies during the simulation together with contextual information coming from sensors and they participate in the state update process implemented in each agency.

_Contextual input scaling problem._ At simulation time-step \( t_n \) internal agencies prepares for potential actions at \( t_{n+1} \) based on distances to front and back neighbours on both same and adjacent lanes at \( t_n \), based on the unchangeable values of personality traits, and based on their internal state at \( t_{n-1} \). However inputs coming from personality factors and are situated, as explained above in \([-1;1]\) interval, whereas these distances are expressed in metres and can vary widely according to instantaneous positions of vehicles on the road. This fact generates the need to scale distance inputs taken from physical environment to normalised values which can be used in conjunction with values of personality factors and with those of internal entities. Yet, a simple normalisation process would not be sufficient since intervals of variation are not constant hence their limits are not fixed values throughout the simulation.

In order to solve this issue, deviation of real distance to neighbours from a minimum safe distance is used. Figure 4-a shows the most general traffic pattern with vehicle of interest \( c \) running from left to right on a double lane road and situated between four neighbours. Distances to these neighbours – \( d_{1r}, d_{2r}, d_{3r}, d_{4r} \) – vary in time and for this reason they cannot be placed in a fixed variation range, hence normalising them is a difficult issue since limits of the variation interval are not constant. Figure 4-b,c shows the scaling procedure for distance between current vehicle \( c \) and front neighbour 1, procedure for all other neighbours being similar.

In this car-following situation an additional point \( s \) is considered as in the Collision-Avoidance car-following model described later in equation (10). This point is situated at the minimum safety distance \( d_{1s} \) to leading vehicle (neighbour 1) within which a collision would be unavoidable in the eventuality that driver of the vehicle in front would act unpredictably, and given an assumed maximum deceleration capability. Distance \( d_{1s} \) is also calculated according to equation (10).
However, in real traffic situations distance between current and leading vehicle is not always $d_{1s}$ as in the ideal Collision-Avoidance case, but it can be either below or above the safe distance, generating a measurable deviation $\Delta_1$ – equation (1), and subsequently a normalised deviation $x_1$, which can fall into two cases.

\[ \Delta_1 = d_{1s} - d_{1r} \]  

Figure 4 Input scaling process: a) unscaled inputs – distances from current vehicle (c) to neighbours; b) current vehicle and neighbour 1 – deviation from optimal/safe distance towards unsafety; c) current vehicle and neighbour 1 – deviation from optimal/safe distance towards safety.

First case, Figure 4-b, is when real distance $d_{1r}$ is below the safe distance ($d_{1r} < d_{1s}$). In this case deviation from ideal point is towards unsafety, and the range of this deviation is between zero – when vehicle c keeps a safe distance $d_{1s} = d_{1r}$ to leading vehicle 1, and a maximum deviation of $d_{1s}$ – when c follows vehicle 1 at a hypothetical $d_{1r} = 0$. In this case deviation from safe distance can vary in the interval $(0;d_{1s})$, hence the value used as denominator for normalised deviation $x_1$ is $d_{1s}$ – equation (2), with resultant values of $x_1$ situated in interval $(0;1)$.

\[ x_1 = \frac{\Delta_1}{d_{1s}} = \frac{d_{1s} - d_{1r}}{d_{1s}} \]  

(2)
Second case, Figure 4-c, is when real distance \(d_{1r}\) is above safe distance \((d_{1r}>d_{1s})\). In this case deviation \(\Delta\) from ideal point is towards safety, hence deviation range is between zero – when \(d_{1s}=d_{1r}\), and a maximum hypothetical deviation of \(d_{4r}\) when real following distance \(d_{1r}=d_{u}+d_{1r}\). In this case deviation from safe distance can vary in the interval \((-d_{4r},0)\), hence the denominator used for calculating normalised value \(x\) is \(d_{4r}\) – equation (3), with resultant values of \(x\) in interval \((-1,0)\).

\[
x_1 = \frac{\Delta}{d_{4r}} = \frac{d_{1s}-d_{1r}}{d_{4r}}
\]

(3)

Overall, the input scaling process for vehicle \(e\) and neighbour \(l\) is described in equation (4), with a resultant scaled (normalised) input \(x_1 \in (-1; 1)\) which can be used in conjunction with the other relevant variables and constants in the process of agency state update.

\[
x_1 = \begin{cases} 
\frac{\Delta}{d_{1s}}; & \text{if } d_{1s} > d_{1r} \\
\frac{\Delta}{d_{4r}}; & \text{if } d_{1s} < d_{1r}
\end{cases}
\]

(4)

Affective agency. The affective system assumed in this implementation uses a dimensional approach on emotions in which several fundamental independent emotional directions bipolar and continuous represent the variety of human emotional responses. Studies in transportation psychology and behaviour (Grimm et al., 2007) found that the space of emotions applicable to drivers consists of three independent emotions: happiness – \(E_H\), drowsiness – \(E_S\) and anger – \(E_A\).

From the implementation point of view emotional space can be represented as a 3-dimensional tuple \(E(E_H, E_S, E_A)\) with \(E_i \in (-\infty; \infty)\), where \(E_i\) are primitive emotions. Computationally the problem generated by infinite emotional intervals was solved following the same approach used for personality: infinite values of emotions \(E_i\) were conveniently limited to finite real intervals \(E_i \in [-E_{max}, E_{max}]\), where \(E_{max}=1\).

Figure 5 shows the influence diagram of action formation process and explains the transfer of driver’s affective features into traffic-related actions. The influence diagram was generated using studies of Clarke and Robertson (Clarke & Robertson, 2005), Lajunen (Lajunen, 2001) and Jovanovic (Jovanovic, Lipovac, Stanojevic, & Stanojevic, 2011) for personality and those of Fiedler and Bless (Fiedler & Bless, 2001), Shinar (Shinar, 1998) and Grimm (Grimm et al., 2007) for emotional features. In terms of potential traffic-related actuation, from the virtually infinite number of possible actions of a driver in traffic conditions the list was reduced to only those found to be of extreme importance (Grimm et al., 2007; Jovanovic et al., 2011; Sarkar, Martineau, Emami, Khatib, & Wallace, 2000): speeding, ignoring priority rules, tailgating and cutting.

Internal dynamics of the SoM affective agency, shown in Figure 6, is an adaptation to SoM driver agent implementation of the general influence diagram presented above, and consists of two main elements: emotional update function and strength update function.

Emotion update function. Several relevant computational models of emotions have been discussed in (Tsankova, 2009). However, in this study emotional update function was implemented starting from the intensity-decay approach described in Cathexis model (Velásquez, 1997). Velasquez assumes that, unless there is some inhibitory or excitatory input, intensity of an emotion decays according to a predefined function in every update-cycle, and after a few cycles it becomes inactive – equation (5).
Influence of affective features on driving actions: a proposed influence diagram.

\[ E_{it} = f \left\{ D(E_{it-1}) + \sum_{k} L_{ki} + \sum_{l} G_{li}E_{lt} - \sum_{m} H_{mi}E_{mt} \right\} \]  \hspace{1cm} (5)

where \( E_{it} \) is the intensity of emotion \( i \) at time \( t \), \( D() \) is the decay function of emotion \( i \), \( L_{ki} \) is the elicitor \( k \) of emotion \( i \), \( G_{li} \) is the excitatory gain that emotion \( l \) applies on emotion \( i \), \( H_{mi} \) is the inhibitory gain that emotion \( m \) applies to emotion \( i \) and \( f \) is the function that places the emotion \( i \) between 0 and its maximum value. This equation is further adapted to fit the dimensional approach on emotions in traffic conditions proposed by Grimm and colleagues who considered emotions to be independent. Inhibitory and excitatory influences emotions have on each other are neglected, and only a single functional entity including contribution of both decay function and elicitors is considered. The three emotions considered in this implementation: happiness, drowsiness and anger (Grimm et al., 2007) increase or decrease at each update cycle as in (6), where \( x_j \) are the scaled inputs corresponding to instantaneous distance-speed relation to the four neighbours. If resultant values of emotions exceed interval \((-1;1)\) then flooring and ceiling functions are activated to limit the peak values to interval’s extremes \(-1 \) and \( 1 \).

**Strength update function.** After the emotional states are updated they are used together with personality traits and scaled contextual inputs for transferring the updated affective state into a strength level which further participates in the bidding process included in non-compromise stage of decision. Update function of the strength is presented in (7).
Affective agency – internal dynamics diagram.

\[
\begin{align*}
E_H(t_n) & = E_H(t_{n-1}) + \frac{1}{4} \sum_{i=1}^{4} x_i(t_n) \\
E_D(t_n) & = E_D(t_{n-1}) + \frac{1}{4} \sum_{i=1}^{4} x_i(t_n)/2 \\
E_A(t_n) & = E_A(t_{n-1}) + P_N + \frac{1}{4} \sum_{i=1}^{4} x_i(t_n)
\end{align*}
\]  \hspace{1cm} (6)

\[
aff_{\text{strength}}(t_n) = \frac{a(t_n) + u(t_n)}{2} \hspace{1cm} (7)
\]

where \( a \) and \( u \) are aggression and unlawfulness levels, respectively, calculated as in equations (8) and (9). Affective strength is also in the interval \((-1;1)\) and for this reason is further shifted up with one unit and normalised, so it eventually falls into interval \((0;1)\) used in the bidding process.

\[
a(t_n) = \frac{E_A(t_n) - P_A - P_C}{3} \hspace{1cm} (8)
\]

\[
u(t_n) = E_A(t_n) \hspace{1cm} (9)
\]

Rational agency. Rational nature of a driver is always concerned with safety, politeness and rule obeying. This agency is targeting optimality from safety point of view, by enforcing safe following distances correlated with vehicle speed. An appropriate way to implement this behavioural pattern is to use one of the existing well-established collision-avoidance car-following (CA) models which generate a prescribed safe behaviour based on manipulation of the standard Newtonian equations of motion. Thorough reviews of various equation-based car-following and lane-changing models, including
collision-avoidance models can be found in (Brackstone & McDonald, 1999), (Kesting, Treiber, & Helbing, 2007).

CA models assume (10) a minimum safety distance within which a collision would be unavoidable in the eventuality that the driver of the vehicle in front would act unpredictably, and given an assumed maximum deceleration capability.

\[ \Delta x(t_n - T) = \alpha v_{f0}(t_n - T) + \beta_t v_{lead}^2(t_n) + \beta v_{lead}(t_n) + b_0 \]  

where \( \Delta x \) is the minimum safe distance between leading and following vehicles, \( v_{lead} \) is the speed of leading vehicle, \( v_{f0} \) is the speed of following vehicle. Empirical parameters of the Collision-Avoidance model are those presented in (Brackstone & McDonald, 1999): unique reaction time \( T=0.75s \), \( \alpha=0.00028 \), \( \beta_t=-0.0084 \), \( \beta=0.784 \) and \( b_0=4.1 \).

CA models were successfully used not only in simple car-following situations, but also in multi-lane traffic environments for lane-changing tasks as part of gap-acceptance models. Gap acceptance models are consistent with their CA counterpart from single-lane car-following models through that they assume a lane-change depends on the existence of an acceptable (safe) gap between current and neighbouring vehicles, i.e. following and leading vehicles on the current and target lanes (Kesting et al., 2007). Usage of the collision-avoidance car-following models in gap-acceptance setups create overall collision free traffic models, and also brings the advantage of compact mathematical formulation, since minimum distance equation (10) can be successfully used simultaneously for both line-changing and car-following.

This study uses an enhanced version of the classic CA approach, Gipps model (11), which provided outstanding results in car-following modelling (Panwai & Dia, 2005) both analytically and numerically.

\[ v_n = \min \left[ v_n(t) + 2.5 A_n \tau \left( 1 - \frac{v_n(t)}{V_{max}^n} \right) \left( 0.025 + \frac{v_n(t)}{V_{max}^n} \right)^{1/2} ; -B_n \left( \frac{\tau}{2} + \theta \right) \right. \]

\[ + \left. \left[ B_0^2 \left( \frac{\tau}{2} + \theta \right)^2 + B_n \left( 2(x_{n-1} - x_n(t) - S_{n-1}) - \tau v_n(t) + \frac{v_{n-1}^2(t)}{B_{n-1}} \right) \right] \right] \]

where \( n \) and \( n-I \) refer to following and leading vehicle respectively, \( v \) represents speed, \( A \) and \( B \) represent maximum acceleration and deceleration capability, \( V_{max}^n \) is the maximum speed at which following driver wishes to travel, \( \tau \) is the reaction time and \( \theta=\tau/2 \) is a safety margin taken by drivers in normal conditions.

**Rational update function.** According to (10) rational agency computes the minimum distance \( d_{it} \) that vehicle \( c \) must keep from leading vehicle (neighbour 1) given current speeds of the two vehicles (avoid tailgating). This is further used in Gipps model to adjust the speed of current car \( c \) with regard to the safety distance, as in equation (11).

In the same time, depending on the physical situation on the road, the possibility of changing lane is also checked by using (10) for current vehicle with neighbours 2 and 3 respectively. In order to avoid cutting (change lane with unsafe gap from the following car) a role inversion is used in Gipps equation: \( c \) is considered leading vehicle while neighbour 3 is considered following vehicle. In order to avoid tailgating (change lane with unsafe gap to the car in front) a second role inversion is used in Gipps equation: \( c \) is considered following vehicle while neighbour 2 is considered leading vehicle.
Thus, output of rational agency is a potential set of actions which, depending on the physical situation on the road, consists of current vehicle’s speed at next time step \( t_{n+1} \) and acceptance/denial of lane changing action.

**Strength update function** is presented in (12). Since rational agency mainly acts in a prescribed manner based on a car-following model, strength of this agency can be assumed to depend on contextual input from neighbour 1 only, and also on values of personality traits. Equation (12) describes the following: the need of rationality increases as following distance falls below the safe distance and decreases otherwise. Also, rationality is expected to increase as personality traits are on the positive side and decrease otherwise.

\[
rat_{str}(t_n) = x_1(t_n) + \frac{P_c + P_A - P_N}{3} \tag{12}
\]

**Reactive agency.** Reactive agency implements driver’s physiological reaction (reflex) to extreme danger. In traffic conditions extreme danger is considered when a collision with vehicle in front is unavoidable given the deceleration capability of current vehicle, the speed difference between the two vehicles, and the distance between them.

**Reactive update function.** Reactive agency is implemented using a standard Finite State Machine (FSM) approach on reactive architectures, with state transitions as in Table 1, where \( \Delta t = t_{n+1} - t_n \) is the simulation time-step and \( d_M \) is the maximum deceleration vehicle is capable of. The agency is implemented in a rule-based approach in which collision possibility is calculated using manipulations of standard equations of motion (13):

\[
\Delta x_{\text{danger}} = \frac{(v_{\text{fail}} - v_{\text{lead}})^2}{d_M} \tag{13}
\]

where \( \Delta x_{\text{danger}} \) is the danger distance below which a collision cannot be avoided given the maximum deceleration capability \( d_M \) of the follower and the speed difference between the two vehicles.

**Strength update function.** Unlike the other two agencies, reactive agency has a binary strength update function which signals a dangerous situation with regard to the relation between current vehicle \( c \) and leading vehicle neighbour 1 (14). If distance \( d_{1r} \), between \( c \) and neighbour 1 is equal or lower than \( \Delta x_{\text{danger}} \), reactive agency generates maximum strength, which translates in 100% chances of winning the competition with other agencies. Actions to be actuated in this case are as follows: the agency proposes a lane change while keeping the existing speed if a gap larger than danger gap exists. If such a gap does not exist the agency proposes full deceleration capability while keeping the current lane.

If distance \( d_{1r} \), between \( c \) and neighbour 1 is higher than \( \Delta x_{\text{danger}} \), danger does not exist, hence reactive agency is not needed. Thus it generates a disqualifying value of strength which will translate in 100% chances of losing the competition with other agencies.

\[
rct_{str}(t_n) = \begin{cases} 
1 & \text{if } d_{1r} \leq \Delta x_{\text{danger}} \\
0 & \text{if } d_{1r} > \Delta x_{\text{danger}} 
\end{cases} \tag{14}
\]
**CURRENT STATE \( (t_n) \)** | **INPUT** | **NEXT STATE \( (t_{n+1}) \)**
--- | --- | ---
Cruise Speed: \( v(t_n) \) Lane No = 1 | Danger Adjacent lane: free | Cruise speed: \( v(t_{n+1}) = v(t_n) \) Lane No = 2
| Danger Adjacent lane: busy | Reduced Speed: \( v(t_{n+1}) = v(t_n) + \Delta t \cdot d_M \) Lane No = 1
Cruise Speed: \( v(t_n) \) Lane No = 2 | Danger Adjacent lane: free | Cruise speed: \( v(t_{n+1}) = v(t_n) \) Lane No = 1
| Danger Adjacent lane: busy | Reduced Speed: \( v(t_{n+1}) = v(t_n) + \Delta t \cdot d_M \) Lane No = 2

Table 1 State transition for FSM-based reactive agency

**K-line selection and actuation.** The three internal agencies do not generate action immediately; they only create the preparedness to generate in the physical domain those effects which are related to them, which can be general sets of actions. K-line selector holds the knowledge base about traffic situations, named in this study “traffic motifs” – Table 2, and indicates to each agency which specific action from the action set is currently suitable. Thus, for each agency only those actions which are relevant for current situation are passed to the bidding process together with agency’s strength.

<table>
<thead>
<tr>
<th>Motif</th>
<th>Description</th>
<th>Lane setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>C current vehicle</td>
<td>single lane</td>
</tr>
<tr>
<td>2</td>
<td>C1 current vehicle and neighbour 1</td>
<td>single lane</td>
</tr>
<tr>
<td>3</td>
<td>C4 current vehicle and neighbour 4</td>
<td>single lane</td>
</tr>
<tr>
<td>4</td>
<td>C14 current vehicle and neighbours 1 and 4</td>
<td>single lane</td>
</tr>
<tr>
<td>5</td>
<td>C12 current vehicle and neighbours 1 and 2</td>
<td>double lane</td>
</tr>
<tr>
<td>6</td>
<td>C34 current vehicle and neighbours 3 and 4</td>
<td>double lane</td>
</tr>
<tr>
<td>7</td>
<td>C124 current vehicle and neighbours 1, 2 and 4</td>
<td>double lane</td>
</tr>
<tr>
<td>8</td>
<td>C134 current vehicle and neighbours 1, 2 and 4</td>
<td>double lane</td>
</tr>
<tr>
<td>9</td>
<td>C1234 current vehicle with all neighbours</td>
<td>double lane</td>
</tr>
</tbody>
</table>

Table 2 Traffic motifs

“Non-compromise” stage – bidding strategy. Bidding process is a key component of the proposed RRA SoM driver agent and represents the computational instantiation of SoM principle of non-compromise, with internal agencies of SoM agent participating in a competition with only one winner. Thus, a bidding process (i.e. an auction-like process) must be implemented instead of a compromise-based conflict resolution mechanism. A truthful bidding strategy based on classical English auction (Cary et al., 2007) is used for the proposed SoM driver agent, i.e. internal agencies bid with their true value of strength – in interval \((0;1)\), and winner is the agency with highest strength.

**Evaluation of SoM driver agent in a traffic behaviour context**

First, the proposed SoM driver agent is evaluated in a standard car-following context against Gipps model, in order to understand how SoM agent, by including both innate behavioural propensities and instantaneous mental states, can generate decisions which deviate from the prescribed optimality (rationality) assumed by conventional car-following models, allowing both biased and adaptive...
behaviour, respectively. Then the agent is evaluated within the traffic motifs used by K-Line selector, in order to test its applicability in and adaptation capability to all possible traffic situations. This second set of simulations creates an insight on agents’ internal decision making process and investigates the influence of contextual inputs and innate behavioural propensities on activation of affective, rational and reactive decisions.

Car-following evaluation

The car-following investigation is derived from one of the most used evaluation methods for computational car-following models (Brackstone & McDonald, 1999). In this approach the vehicle of interest, acting based on a built-in car-following model, follows for a certain distance on a straight single-lane road segment a leading car travelling with a prescribed speed pattern. Motion of leading and following cars is then recorded and their distance trajectories, instantaneous speeds and distance headways investigated in order to evaluate the car-following behaviour.

Given that in this case the model to be evaluated is a behavioural one, we use a setup with a 1000 m single lane road segment, slightly longer than the range of 160 to 200 metre road segments used by conventional models, in order to allow the mental features of driver agent to evolve towards desired decision-making capabilities. Leading vehicle runs at a constant speed of 40 km/h and following vehicle is controlled by a SoM driver agent which can be initialised with different personality patterns.

Figure 7 shows the SoM driver agent initialised with: a – maximum negative personality features \( P = (N/A, -1, -1, -1, 1) \), b – balanced personality \( P = (N/A, 0, 0, 0, 0) \) and c) maximum positive personality features \( P = (N/A, -1, -1, -1, 1) \). In each situation instantaneous speed and distance headway for both SoM driver agent and Gipps follower are computed.

In all cases Gipps follower has the expected rational/optimal following behaviour. It rapidly adjusts its speed to a constant value of 40km/h identical to that of leading car, and manages to keep a minimum distance headway of approximately 12 metres to leading car, which is optimal from a safety-speed pointy of view, as described in (10).

For the SoM follower, decisions actuated in physical environment (speed) are taken at each simulation step by the current dominant internal agency, being influenced by agent’s personality.

The agent with extreme negative personality traits, Figure 7-a, has an oscillating following behaviour. Rational decision is absent throughout the simulation with only affective (96.11% of the time) and reactive (3.89%) decisions governing its actions. Repeatedly, affective agency takes control and dictates rapid speed increase over the safety limit to a dangerous distance to leading car triggering activation of reactive agency (emergency breaking) in order to avoid collision.

The agent with balanced personality has a behaviour closer to optimality, with affective agency still becoming active 29.83% of the time; however acceleration rate is lower, reactive breaking only occurring 0.055% of time and speed at which the reaction is triggered is significantly lower than the previous case. For the rest of 69.61% of time control is taken by rational agency which holds the vehicle on an optimal following pattern similar to that provided by standard Gipps follower.

The agent with positive personality traits acts at optimal end of behavioural spectrum with rational agency being in control 100% of the simulation. Resultant car-following behaviour is in this case optimal and identical with that generated using standard Gipps model.

As expected, agent with positive personality traits acts at optimal end of behavioural spectrum with rational agency being in control 100% of the simulation. Resultant car-following behaviour is in this case optimal and identical with that generated using standard Gipps model.

From a car-following perspective it was shown that driver behaviour varies widely when mental features are included in simulation, producing expected deviations from the rationality (optimality) assumed by Gipps model. Also, from SoM agent perspective personality biases determine variations in the amount of activation for affective, rational and reactive agencies confirming the dependency of activation amount of each agency on agent’s personality type.
The three types of personality considered above, suggest that negative personalities tend to activate more the affective agency, which also triggers increased activation of reactive agency as result of unsafety, while positive personalities favour activation of rational agency. A more detailed view of this dependency is shown in Figure 8 which summarises an extended set of simulations where agent’s personality was swept from most negative to most positive. Results confirm the above assumption, however, an equilibrium point between affective (towards unsafety) and rational (towards safety) dominance is not situated in the middle of the two personality extremes, but rather is biased towards the negative side in a range belonging to interval (-0.6; -0.2).
Figure 8 Standard car-following setup: agency activation rate (percentage of simulation time) versus personality type.

Since SoM agent takes as inputs distances to all neighbours a biased activation of internal agencies is not unexpected in this particular situation when only neighbour 1 is taken into account. Activation of affective agency is based on emotional update function (6) which depends on contextual data coming from physical distances to neighbours. Accordingly, higher increase rates for emotions are expected when inputs from all neighbours contribute to update function, whereas for a single neighbour only one input from the set of four contributes to emotional update. From an adaptation point of view this can be explained through that there is less potential stress for the SoM agent which could raise affective agency level of strength, giving more chances for rational decision. Hence, even if the agent has negative personality traits, lack of pressure coming from the traffic context leaves affective agency deactivated.

In order to test this adaptation assumption, the standard car-following setup is extended to simulations with two neighbours (1 and 3), where c is the SoM driver agent, 1 is a costant speed vehicle and 3 is a Gipps follower.

Results, Figure 9, show a similar car-following behavioural pattern to those obtained for simple car-following setup, confirming resemblance of agent’s behaviour to expected real-life situations. From the point of view of SoM agent, Figure 10 also confirms the agency activation pattern (adaptation) found in standard car-following setup, with the balanced activation biased towards negative side of personality traits, though a lower bias was recorded in this case. Potentially this is due to the extra neighbour – a second source of stress – whose influence adds to emotion update function and increases the affective agency activation rate for the same personality type.

However, a more detailed investigation of internal agencies activation pattern – adaptation – for SoM driver agent is needed for drawing a clearer conclusion. In order to do that, SoM driver agents must be studied outside the limited context assumed by standard car-following evaluation, in traffic situations (motifs) in which all participants (vehicle of interest and its neighbours) are SoM agents. In this case both leaders and followers are not ideal – i.e. Gipps or prescribed speed pattern – but SoM agents with unpredictable behaviour guided by both personality and traffic context.
Figure 9 Modified car-following setup: instantaneous speed and time headway: a) negative personality traits, b) balanced personality traits, c) positive personality traits.

Traffic motifs evaluation – adaptation

Second set of experiments evaluates the SoM driver agent in traffic situations in which both vehicle of interest and its neighbours are SoM agents. As explained earlier in the paper, a set of traffic motifs can be taken into account in order to describe the relevant traffic context used by SoM agent’s internal agencies – Table 2. These situations can be considered as primitive traffic patterns, which multi-agent traffic simulations of any complexity can be further based on.

The methodology used for this investigation is similar to the one used in the previous section for standard car-following evaluation. In each situation both vehicle of interest – c – and its neighbours are SoM driver agents initialised with certain values of personality traits. For each traffic motif activation rate of internal agencies for driver c is observed in relation with its personality type.

Results confirm that activation rate of each internal agency is consistent with both innate and contextual inputs. Figure 11 (motif 1 – no neighbours) clearly shows that lack of interaction with neighbours generates a behaviour close to rationality (optimality) even when personality traits are at the negative extreme. Despite personality factors participate in emotional update function, there is no contextual addition due to lack of neighbours, hence resultant decision is mostly rational even for the most negative personalities.
Figure 10 Modified car-following setup: agency activation rate (percentage of simulation time) versus personality type.

Figure 11 Agency activation rate vs personality type: Motif 1.

Figure 12 shows activation patterns for motifs 2 to 9, with increasing amount of interaction: from vehicle of interest and one neighbour to vehicle of interest and all four neighbours. Activation pattern is consistent with observations from previous section, showing an increase in activation of affective agency with the amount of interaction with neighbours (i.e. number of neighbours). An increase in interaction with neighbours translates into more contextual inputs which contribute to emotional update function in addition to contribution of personality traits; thus activation rate of affective agency decrease slower with positiveness of personality when interaction with neighbours increases.
Figure 12 Agency activation rate vs personality type: motifs 2 to 9.
This equals in term of graphical representation with a shift and an enlargement of activation equilibrium interval from a biased (-0.4;-0.2) for motifs with one neighbour to a symmetrical (-0.4,0.4) for motifs with three and four neighbours.

Apart from the affective-rational discussion, agent’s consistency also results from activation pattern of reactive agency. Motifs with high interaction with front neighbours (2,5 and 7) produce in conjunction with affective activation, as result of unsafety, higher rates of activation for reactive agency when compared to motifs with high interaction with back neighbours (3,6 and 8). This is due to the fact front-free motifs provide either free drive or free adjacent lane, thus chances of collision with front neighbour decrease, and so does the need of emergency breaking generated by reactive agency.

![Figure 13 Activation landscape over traffic motifs and personality types: a) affective agency; b) rational agency; c) reactive agency.](image)

Agency activation landscape. In order to provide a better understanding of overall agency activation pattern in relation with both personality type and traffic motif, a representation as a 3-dimensional tuple (activation-personality-motif) is proposed. Figure 13 shows in a comprehensive and intuitive manner how each internal agency activates over the “landscape” generated by agents with various personalities situated in various instantaneous traffic situations. Activation rate of affective agency (a), as opposite to rational agency (b), increases overall towards negative personality and motifs with high interaction with a global maximum in the high-interaction<>negative-personality corner, while in the same time it decreases at a lower rate towards the high interaction side. Activation of reactive agency has also an overall increasing pattern towards negative personality and motifs with high interaction, with high values in the high-interaction<>negative-personality corner. In the same time the overall activation landscape shows
ridges along motifs with high-forward<>low-backward interaction and valleys along those with high-
backward<>low-forward interaction respectively.

Multi-agent evaluation – traffic density and personality mix

Another question naturally arising is how the SoM driver agent behaves in more complex traffic scenarios. In the above paragraphs, the agent was studied from a standard car-following perspective, and it was also shown how it behaves in a set of fundamental traffic motifs. However, the usual day-to-day traffic situations are beyond this level of complexity and they involve various densities, from a traffic perspective, and various behavioural mixes of the individual personalities, from a driver perspective. The 1000 metres double-lane road segment used for the car-following and traffic motif evaluation is now used for traffic densities ranging from 50 to 200 vehicles per km. The traffic performance resulting from the interaction of individual driver actions is measured through the average speed over the road segment for all vehicles in two scenarios.

In the first scenario, all drivers have identical behaviour: i.e. identical personality traits. This equals with considering populations of drivers which are purely homogeneous from a personality point of view. Simulations are run for three types of driving behaviours: negative, balanced and positive. Figure 14 shows the average speeds for each behaviour type for various traffic densities. From a traffic perspective there is an obvious drop in the average speed with the increase of density, for all behaviours. From the agent perspective, it can be seen that positive personalities allow higher average speeds. This is consistent with the individual evaluation of the driver agent, where positive personality triggered the activation of rational internal agency, i.e. the rational behaviour. However, the difference between the three types of population decreases as the density increases, arguably, because the road saturation is reached at a density of 170 vehicles/km. Thus, traffic performance is limited by the road capacity, not by driver behaviour. However, in this scenario an ideal situation is presented, with drivers having identical personalities, whereas in real life populations of drivers have various degrees of heterogeneity.

The second scenario considers this aspect, and simulates populations of drivers with normal distribution of personality traits in relaxed traffic conditions (density of 100 vehicles/km). Various degrees of heterogeneity are modelled by considering normal distributions with \( \mu=0 \) and \( \sigma \in [0,1] \). This results in a range of populations from pure balanced homogeneous populations (\( \sigma=0 \)) to highly heterogeneous populations (\( \sigma=1 \)). Given that the personality traits are computationally implemented in the finite interval \([-1;1]\) a population with \( \sigma=1 \) could approximate an uniform distribution. Figure 15 shows the changes in traffic performance when different values of \( \sigma \) are considered. Results indicate that the fluency of traffic can be jeopardised as the heterogeneity increases. It can be inferred that the more diverse are the interacting drivers the more impediment they create for traffic flow, resulting in an overall inefficient collective behavioural pattern. From a different point of view, it can be seen that the average speeds recorded for heterogeneous populations are in general lower than those recorded for the homogeneous population of the same size (traffic density). At a traffic density of 100 vehicles/km the worst case of homogeneous population, corresponding to extreme negative personalities, generates an average speed \( v=29.2 \) km/h. In comparison, the most heterogeneous population generates an average speed \( v=22 \) km/h.

It can be concluded from the above results that a better traffic outcome is obtained when drivers have homogeneous behaviour, be it a negative one, rather than acting heterogeneously. However, such a collective driving strategy is hardly achievable in real life, since individual personalities/behaviours in a population always show a certain degree of heterogeneity, coming nevertheless from a much needed diversity of human nature.
Figure 14 Traffic performance for various traffic densities: homogeneous populations of drivers with positive, balanced and negative personality traits.

Figure 15 Traffic performance for various degrees of heterogeneity, and traffic density of 100 vehicles/km.

Comparison with real data

The SoM driver agent is also tested in a realistic traffic context on real road networks. Real road network data are extracted from the maps of Melbourne area (courtesy of Google Earth and Open Street Maps) and used with suburb population distribution data taken from Victorian Government population bulletin.
(Government, 2010) and road traffic statistics from Australian road traffic association (Austroads, 2013) and Victorian (Melbourne) road traffic authority (VicRoads, 2012).

The investigation is conducted on a set of populations with different levels of heterogeneity, i.e. normal distribution of personality traits with $\mu=0$ and $\sigma \in (0; 1]$. The realistic distribution of personality traits for Melbourne drivers is considered normal with $\mu=0$ and $\sigma=0.7$ based on a number of studies in personality theory (Allik & McCrae, 2004; McCrae & Terracciano, 2005; Schmitt, Allik, McCrae, & Benet-Martínez, 2007). In these studies the authors showed that personality traits for Australian population has a standard deviation situated towards the higher end (higher heterogeneity) of the standard deviation interval from a number of 56 countries around the world. In this study we consider Melbourne population statistically similar to the Australian one. The aggregate average speed over the inner and outer freeway roads of Melbourne (Figure 16) is calculated and compared to the real average speed reported by road traffic authorities. The real population data, the real road network and the recorded average speed are those corresponding to year 2010 (Figure 17).

![Figure 16](image16.png) Melbourne inner and outer freeways network as extracted from Open Street Maps. ■ – roads with speed limits of 100km/h, ■ – rail network.

Figure 18 shows the simulated average speeds for various degrees of heterogeneity, including a standard deviation of 0.7, which corresponds to the assumed realistic population of Melbourne. From one point of view, results show that traffic performance decreases with the population heterogeneity, confirming in a realistic context the results obtained for a single road segment. From a different point of view, the average speed generated by the realistic population of Melbourne (71.41 km/h) is consistent with the real average speed (76 km/h) recorded by traffic authorities, with a 6.03% deviation from real data. This demonstrates that the proposed SoM agent can be successfully used in a realistic context, generating traffic outcomes very close to the recorded traffic data. However, a deviation exists, which can be the result of several factors. First, the road network was obtained by accessing Open Street Map website (www.openstreetmap.org) and exporting the area of interest. Since Open Street Map is an open
source system updated by volunteer contribution, certain differences from real road maps may exist, potentially introducing a subsequent amount of inaccuracy. Second, the population of Melbourne was considered as having similar statistical distribution of personality features to that of the whole Australian population, fact that could introduce as well a certain degree of inaccuracy.

Figure 17 Yearly aggregate average speed for Melbourne freeway roads. Data from (Austroads, 2013) and (VicRoads, 2012).

Figure 18 Aggregate average speed for Melbourne freeways roads. SoM driver populations with various degrees of heterogeneity.
Conclusions

In this study we proposed a non-hierarchical hybrid agent architecture based on Minsky’s “Society on Mind” model of human mind and cognition, assuming that such an approach would allow modelling of human behavioural diversity and adaptation capabilities in cognitively demanding contexts. We implemented the proposed architecture in such a context as a car driver, and we showed that the resultant SoM driver agent design is capable of producing expected driving behaviours for driver agents with a variety of personality features in a wide range of various traffic situations.

The SoM driver agent was tested in a set of traffic contexts in order to demonstrate its usability. First, the driver agent was evaluated in simple car-following situations and demonstrated consistency with traffic expectations from a standard car-following point of view. Also, an investigation of agent’s internal agency activation pattern (adaptation) demonstrated the consistency of its response with both contextual and non-contextual inputs. Second, the driver agent was evaluated in a multi-agent setup for various traffic densities and for various behavioural mixes. Results were consistent with the individual evaluation performed in the car-following setup and provided important information for establishing potential collective driving strategies/behaviour that generate high traffic performance. Third, the driver agents were used in a realistic context on the real road network of city of Melbourne. The traffic performance generated by the artificial driver drivers was consistent with the real data obtained and published by road traffic authorities.

The capabilities demonstrated by proposed SoM agent architecture create the foundation for usage of non-hierarchical hybrid agents in many other problems of interest, wherever human decision-making involves balancing multiple cognitive capabilities. In relation with this study, further work could point to more complex traffic situations for purposes such as system-level investigation of traffic psychology and behaviour, or for assessment of traffic performance and safety measures, where conventional models of steady state and agents without the capability of recreating the behavioural variety of human drivers may generate erroneous assessment outcomes. However, investigations in other fields of activity such as agent-based social simulations, artificial life and societies or robotics can be expected to produce significant insights on various phenomena or solve decision-related issues.

References


