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A Model of Team Decision Making using Situation Awareness

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Abstract. In order for agents to successfully make decisions about task allocations within a team, two elements are essential: (1) a good judgement of the situation and (2) once the situation is known have a good decision making process to derive and assign tasks that should be performed. Within research on agent systems, little work has been done on the combination of the two. In this paper, a human-based situation awareness model is combined with a decision making procedure (which incorporates task identification and task allocation). In order to show that the approach is able to produce good results, it has been evaluated in a case study within the domain of fighter pilots. More specifically, enemy fighter pilot decision making is modelled, for the purpose of using intelligent agents in the enemy role in virtual simulation training. Simulation runs using the model show promising results.

Keywords: Situation Awareness, Computational Model, Team Decision Making

1. Introduction

In order for agents to be able to perform well in decision making, one crucial aspect is that such agents have sufficient knowledge about the situation. Endsley [2] states that "*in most settings effective decision making depends on having a good understanding of the situation at hand*". This "understanding of the situation at hand" is often referred to as *situation awareness* (see [2]). Of course, once good situation awareness is established, the effectuation of a decision is not a trivial matter either, especially in settings whereby multiple agents play a role, for instance when agents cooperate in teams. Crucial elements hereby include the allocation of tasks to agents as well as the monitoring of the progress of their task execution (and thus constantly maintaining a good understanding of the situation).

Within research in (multi-) agent systems both aspects that have been mentioned above have been rigorously investigated. Models have been developed that focus on situation awareness (see e.g. [5;7;10]) enabling an agent to make an accurate judgment of the situation and make the right decisions. Furthermore, ample approaches have been developed that aim towards effective cooperation in teams, making sure that tasks are allocated to the right agents that are part of these teams (see e.g. [4;9]). The integration of the two however has not received much attention.

In this paper, an integrated framework is presented for situation awareness in combination with decision making in teams. Hereby, the model has been created for domains where centralized decision making is adopted within the team (i.e. one agent is in charge). The framework includes a situation awareness model that has previously been developed based upon psychological theory (cf. [5]), and uses the output of this model to decide upon a tactic that should be followed. Again, the latter part has been inspired by psychological theory (more in specific, the theory of Naturalistic Decision Making by Klein [8]). Given this selected tactic, the tasks accompanying the tactic are derived and appropriate agents are allocated that eventually execute the task. Within the model, a continuous monitoring of the situation is present, during which the suitability of the current tactic is monitored. The model yields an intervention once another tactic appears to be more promising (e.g. due to changed circumstances or failure of task execution). The model has been evaluated in the domain of fighter pilots (more specifically in air-to-air combat situations). In this context, team based decision making is modelled as a process that aims at the combined use of aircraft and weapons in order to defeat or gain advantage over an adversary.

This paper is organized as follows. In Section 2 the theoretical background is sketched that underpins the developed model. The model itself is described in Section 3. Section 4 presents the case study using which the model has been evaluated, and the results are presented in Section 5. Finally, Section 6 is a discussion.

2. Theoretical Background

One of the sources of inspiration for the work presented in this paper comes from the domain of psychology. Tactical decision-making is the cognitive process leading to the selection of an appropriate tactic among multiple options. For the current purposes, tactical decision-making is defined as the mental process by which agents recognise, analyse, and evaluate information about themselves, the tactical situation, and the operational environment, leading to a decision. In more formal and general terms, one may break down the decision making process in the following sub-tasks or sub-goals: option generation (based upon the judgment of the current situation), option prioritisation, evaluation of options, and option choice.

The aforementioned definition clearly aims at individual decision-making and not at 'team decision-making' (also called 'distributed decision-making') in which the team (e.g. the pilots flying a formation of fighter aircraft) needs to agree on the actions to be taken. This type of decision-making is called distributed because none of the team-members possesses all the information relevant to the decision, in other words, this information needs to be communicated. A quick decision-making mechanism is called 'recognition-primed decision making' [8], presumably based on pattern matching between an activated 'mental solution' and the real-world situation or problem. A large part of this recognition-primed decision-making process proceeds 'automatically', subconsciously, without explicitly activating the separate elements, such as observations, constraints, steps to resolve the problem, and sub-goals. Recognition primed decision making process is quick, relatively immune for workload and effortless, such that multi-tasking is possible. A much slower individual decision-making process comes into place when novel, unfamiliar problems are presented to a human. Such problems, often with incomplete information, require so-called inductive strategies, such as backward-reasoning, sub-goal-setting etc. Such conscious cognitive processes are sensitive for stress, effortful (no spare capacity for other tasks) and prone to error.

In team decision-making none of the team-members has all the information required to execute the subsequent tasks that are required to accomplish the mission. Therefore, team decision-making implies that recognition-primed decision-making is always hampered to some extent. After all, information that is missing at one individual is present at another individual and needs to be made explicit through communication. This is what is called team-co-ordination. Through team-co-ordination, a potentially quick process (recognition-primed decision-making) thus becomes a slow process. One or more elements of the solution (e.g. an observation, a constraint, a tactic, or a sub-goal) need to be communicated. Obviously, co-ordination between team-members is central in achieving the goals that cannot be achieved by individual agents by themselves. As well as understanding team co-ordination at a behavioural level, it is important to be aware of the level of underlying cognitive processes, of which, according to Klein [8], the most important are: (1) Control of attention; (2) Shared situation awareness; (3) Shared mental models; (4) Application of strategies and heuristics to make decisions, solve problems, and plan; (5) Theory of Mind (or meta cognition, i.e. thinking about (other team members' or opponents') thinking).

3. Multi-Agent System

Section 2 has been used as a source of inspiration to develop a model for team decision making. The overall architecture consists of two types of agents: (1) a task allocation agent, and (2) a task execution agent.

Figure 1 presents the agent that is in charge of the team and responsible for assigning the tasks to other agents (i.e. the task allocation agent). In the figure, it can be seen that the agent comprises of four components. First of all, a component is present which creates a judgment of the current situation (the *situation awareness* component). Thereafter, this information is forwarded to the component *tactic selection*, which takes this situation into account when selecting the most appropriate tactic. The tactic is then forwarded to the *task determination* component which derives the tasks to be executed given this tactic. Finally, the component *task allocation* determines which agents to allocate to these tasks. This task allocation is then forwarded to the appropriate agents.

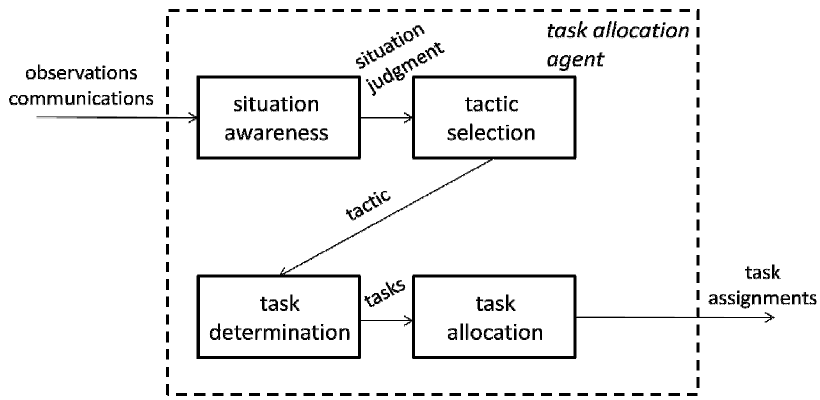

Figure 1. Task allocation agent architecture

The architecture of the agents that execute the tasks is straightforward. Essentially, the agent receives as input observations and communications with respect to the situation as well as the assignment of the task. A *situation awareness* component compiles a judgment of the situation again, which is then forwarded to the *task execution* component. This component uses both this situation and the assigned tasks to come to concrete actions that are performed in the world.

Below, each of the components are explained in more detail.

3.1 Task Allocation Agent

First, the components within the task allocation agent are described.

3.1.1 Situation Awareness. The first element in the model of the task allocation agent involves the creation of a good situation awareness within the agent in charge as also highlighted in Section 2. In order to do so, the model presented in [5] has been adopted which is based upon the theory proposed by Endsley [3]. In the theory, situation awareness is said to include the perception of cues, the comprehension and integration of information and the projection of information for future events. For the sake of brevity, the full details of the model are not explained (see [5] for these details), but essentially, the model comprises of four parts:

1. Formation of simple beliefs about the current situation based upon observations and communications.
2. Integration of beliefs into more complex aggregated beliefs about the current situation.
3. Generation of future beliefs based upon the complex beliefs.
4. Determination of observations and communications to be performed given the current set of complex beliefs and future beliefs (communication is used to create a good shared situation awareness as expressed by Klein [8]).

In order to perform these steps, knowledge is present within the model that expresses how the various elements are connected: what observations lead to simple beliefs, how simple beliefs influence each other, how complex beliefs are influenced by simple beliefs, and how complex beliefs result in future beliefs. These influence relations are expressed by means of weights of connections between these elements. An algorithm then derives the new activation values of the states based upon the incoming observations and the old values of the states in combination with the weights as described above. This algorithm has anytime behavior. The activation levels of the complex beliefs act as judgment of the current situation and are output of this component.

3.1.2 Tactic Selection. The second component concerns the decision making process to decide upon a tactic to follow and essentially represents the fourth aspect identified by Klein s put forward in Section 2 (i.e. application of strategies and heuristics to make decisions, solve problems, and plan). For this purpose, the following decision rule is used inspired by a decision making model as proposed in [6]. In order to model this process, the LEADSTO language has been used (cf. [1] which is a temporal language in which the temporal relations can be defined in the form of rules that can be executed. Let α and β be state properties. In LEADSTO specifications the notation $\alpha \twoheadrightarrow_{e,\ f,\ g,\ h} \beta$, means:

> *if state property* α *holds for a certain time interval with duration* g*, then after some delay (between* e *and* f *state property* β *will hold for a certain time interval* h.

A specification of dynamic properties in LEADSTO format has advantages that it is executable and that it can often easily be depicted graphically. LEADSTO has been used to model different kinds of cognitive processes with success. For more details of the LEADSTO format, see [1]. As all of the temporal relations used in the model are of the form $\alpha \twoheadrightarrow_{0,0,1,1} \beta$, the notation $\alpha \twoheadrightarrow \beta$ will be used instead.

The first rule derives suitable options for a tactic. Options are suitable in case they are associated with a certain complex belief C1 with a current activation value above zero.

complex_belief(C1, V1) & V1 > 0 & is_option_for(C1, T) $\twoheadrightarrow$ possible_option(T)

The second rule expresses an overall feeling associated with this option, called a somatic evaluation value following (cf. [5], which is based upon theories from psychology again) which is highly dependent upon the relevance of the option for the goal in combination with the activation level of the specific goal. Note that this rule expresses a variant with two goals, but in general n goals could be present.

possible_option(T) & somatic_value_for(G1, T, SV1) & has_value(G1, W1) &
somatic_value_for(G2, T, SV2) & has_value(G2, W2) ↠
somatic_evaluation_value(T, W1/(W1+W2) * SV1 + W2/(W1+W2)* SV2)

Next to a feeling, a rational utility is also provided with respect to the tactic which is independent of the emotions of the agent. This is purely dependent upon the activation value of the complex belief in combination with the utility for the tactic with respect to the complex belief:

possiblie_option(T) & complex_belief(C1, V1) & complex_belief(C2, V2) &
utility(C1, T, U1) & utility(C2, T, U2) ↠
option_utitlity(T, U1*V1/(V1+V2)+U2*V2/(V1+V2))

Finally, the two values are combined into a single evaluation value based upon the rationality of the agent (the more rational, the more weight is attributed to the rational utility of the tactic).

somatic_evaluation_value(T, V) & option_utility(T, U) & value(rational_ration, R) ↠
option_preference(T, R*U+(1-R)*V)

From this ranking of preferences for tactical options results a single most preferred option (i.e. the one with the highest value), which is then forwarded to the next component.

3.1.3 Task Determination. Once a tactic has been selected, a workflow needs to be derived that expresses what tasks accompany the specific tactic to be executed (again following aspect (4) identified by Klein). For this purpose, a workflow representation is used that expresses the ordering in which tasks should be performed within the tactic as well as the requirements associated with each of the tasks (i.e. requirements with respect to the allocation agent). Formally, each task is defined by means of the attributes listed in Table 1. The last element in the table is the output of the component, namely the schedule for the tasks. Note that the additional information is also passed on to enable the finding of a suitable task allocation.

Table 1. Task specification language

Predicate/Sort	Explanation
TASK	Representation of a task.
TIME	Representation of time.
REQUIREMENT	The task allocation requirements can be a complex domain dependent term.
task_preceded_by: TASK x TASK	A task is preceded by another task which should be completed before the task can start.
task_duration: TASK x TIME	The duration of a certain task.
task_allocation_requirement: TASK x REQUIREMENT	The task has a specific allocation requirement.
task_scheduled_from_to: TASK x TIME x TIME	A task is scheduled from a certain start time to a certain end time. Note that the difference should be equal to the task duration.

3.1.4 Task Allocation

Once the tasks have been expressed, an allocation should be found that fulfills the allocation requirements as expressed in the workflow. Of course, there might still be many possible configurations left. Therefore, as an additional criterion the utilization of resources is used (this could be both in terms of mental as well as physical resources). Table 2 expressed the information that is used by the component. Based upon this information, the set of possible allocations is determined. All combinations of agents to tasks are generated for which all agents fulfill the requirements of the tasks they have been allocated to. Thereafter, the following algorithm is executed:

Algorithm 1. Determine allocation

```
For all possible allocations TA
    current_score(TA) = 0;
    For all agents that are part of task allocation TA
        For all resources R that the agent has
            Calculate the prospected resource utilization given the current task allocations
            and current resource utilization.
                if the prospected resource utilization is above the maximum
                        Set current_score = high
                else
                        Calculate the score on the evaluation function.
                        Add the score to current_score(TA).
                end
        end
    end
end
Select the task allocation with the lowest value on the current score.
```

The algorithm essentially determines whether the task allocation does not result in any exceeding of resources (otherwise the score is set to a very high value in case it will only be selected if no other option besides the exceeding of resources is available) and calculates the score using a particular evaluation function. Various evaluation functions can be present. In this case, two evaluation functions are proposed: (1) the minimization of the overall resource utilization (then the score used above is equal to the prospected resource utilization), or (2) minimization of the percentage of utilization (the score equals the division of prospected resource utilization by the maximum value). Using such an evaluation function involves the reasoning about the other team members (i.e. a for of theory of mind) which is the fifth point made by Klein.

Table 2. Allocation information used

Predicate/Sort	**Explanation**
fulfills_requirement: AGENT x TASK x REQUIREMENT	The agent fulfills the requirements for the task (e.g. sufficient education).
current_resource_utilization: AGENT x RESOURCE x VALUE x TIME	The current utilization of a certain resource by the agent.
required_resource_utilization: AGENT x TASK x RESOURCE x VALUE	The amount of resources required for the agent to enable the execution of the task.
prospected_resource_utilization: AGENT x RESOURCE x VALUE x TIME	The prospected usage of a certain resource by the agent, given that certain additional tasks are assigned to the agent.
maximum_resource_utilization: AGENT x RESOURCE x VALUE	The limit of the agent's capabilities.
task_allocation: TASK x AGENT x TIME x TIME	An agent is allocated to the task during the specified interval.

3.2 Task Execution Agent

The details of the component of the task execution agent are quite similar to those in the task allocation agent. The model for situation awareness is completely reused and the second component (task execution) is performed using the same model as used to derive tactics in the task execution agent. Of course, hereby the options are actions that can be performed and the goals in this case indicate the completion of the tasks.

4. Case Study

In order to evaluate the model proposed in Section 3, a case study has been conducted. This concerns a study in the domain of fighter pilots. In this particular case, there are four fighters active, i.e. a real, manned, formation (BLUE) and an agent controlled formation (RED), each formation consisting of a 'flight lead' and a 'wingman', and two opponents. It is assumed that both formations have aircraft that are capable of beyond-visual-range engagements. This, in turn, means that pilots may only 'see' each other via their on-board radar or via their Radar Warning Receiver (RWR). The latter device warns the pilot as soon as it receives radiation from the opponent's radar. More specifically, the aircraft's RWR may signal the pilot that: (1) the opponent's radar is merely *searching* for targets, or (2) that the opponent's radar is actually *tracking* the aircraft, meaning that the position of the aircraft is tracked over a substantial period, which in turn may indicate that the opponent will shoot at the aircraft as soon as the opportunity arises.

When the two formations encounter each other, the leader and the wingman of the agent controlled RED formation should decide upon the tactical manoeuvres that they should execute, in this case manoeuvre A and manoeuvre B. These manoeuvres fall under the heading of air-to-air tactics. In order to select a tactic, dedicated domain information has been inserted as knowledge in the *situation awareness* component of the model (by means of elicitation from experts). This knowledge is e.g. whether the RED flight lead or wingman is searched or tracked by the BLUE formation and the spatial configuration of the BLUE formation (mutual separation, altitude difference). Based upon the judgment of the situation, the RED flight lead selects one out of three tactical options: (1) continue straight and level flight; (2) tactical manoeuvre A, and (3) tactical manoeuvre B. Each of these tactical manoeuvres consists of a number of elementary tasks: *fly_to_position(x,y) 180_degree_turn, 90_degree_right_turn*, *90_degree_left_turn* and *continue_straight_and_level_flight*. These tactical manoeuvres were expressed in the form of a workflow as specified in Section 3. Furthermore, the requirements were composed in such a way that only one aircraft (the RED flight lead or the RED wingman) would be assigned to the task. These requirements involved the fact that the agents were being searched or tracked, and their relative positions. More details with respect to this case study can be found in Appendix A [11].

5. Simulation

In this section, simulation of the agents' behaviour is given. To this end, the case study was implemented in Matlab. A scenario was defined as presented in Section 4. Each point in time, the lead agent's situation awareness was updated based on available observations from the world and the agent's mental model of the relevant beliefs and tactics in the environment.

In order to enable a simulation of the agents, a world model has also been implemented. The model essentially consists of the x and y position and the heading of the agents which change based upon the actions performed by the agents. For example, when an agent had to execute the task to go to position 1, the x and y coordinates of the agent were adjusted towards position 1. The world model also determines what observations the agent receives as input for the situation awarenss model, this includes information about whether the agent is being searched by the opponent (as indicated in Section 4) or tracked (as also expressed in Section 4). This was made dependent upon the relative position of the fighter planes (distance and angle). A very simple radar model was implemented for this purpose:

$$\begin{aligned} p_{searched}(i, j) = {} & w_{distance}(1 - (distance(i, j) / search\_range)) + \\ & w_{angle}(1 - (angle(i, j) / search\_angle)) \end{aligned}$$

For tracking the same equation has been used, except that tracking can only occur in case a successful search was encountered, and the range is set to a lower value.

Table 3. Initial values of the simulated scenario

Parameter	Value
scenario time	30
Position opp A	5, 1
Position opp B	10, 1
Position lead	5, 20
Position wingman	8, 25
search_range	10
track_range	2
search_angle	30
track_angle	30

The simulation settings are presented in Table 3, and include the starting position of the agents and the starting position of the opponents. Also, the table presents the values regarding the search and track behavior of the opponent. Note that the scenario is not deterministic as the detection probabilities play an important role. For analysis, the behaviour of the agents within the multi-agent framework was compared to that of agents within a framework where tactics are randomly selected as well as a fixed continue flying tactic. More specifically, measurements were performed to see how many times the agents were searched and tracked as this is the performance indicator for such tactics. The scenario was executed 100 times. The results are presented below.

5.1 Results

For comparison of the three models (intelligent tactic, random tactic and fixed continue flying tactic), the total number of times that both agents were searched and the total number of times that both agents were tracked were calculated.

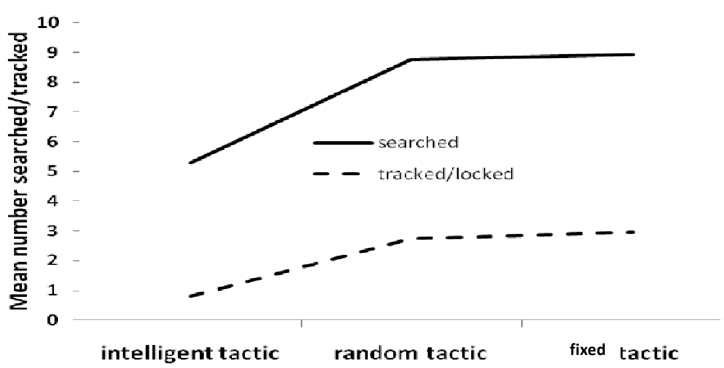

Figure 3. Mean number of times that the flightlead and wingman are either searched or tracked/locked

In Figure 3 the results are graphically represented. A repeated measures analysis (Huynh-Feldt) was performed, which showed that the number of times the agents were searched was significantly less for the intelligent tactic selection (*M*=5.29 *SD*=2.17) as compared to the random tactic selection (*M*=8.75, *SD*=1.87) and fixed continue flying tactic selection (*M*=8.94, *SD*=1.87; $F(2, 99)=115.83$, $p<0.001$). Paired t-tests were conducted to compare the separate models. A difference was found between the intelligent tactic selection and the random tactic selection ($t(99)=-12.53$, $p<0.001$) as well as fixed tactic selection ($t(99)=-13.33$, $p<0.001$).

Also, analysis of the number of times that the agents were tracked showed that there was a significant difference between the intelligent tactic selection (*M*=0.8, *SD*=0.98), the random tactic selection (*M*=2.73, *SD*=1.48) and fixed tactic selection (*M*=2.95, *SD*=1.47; $F(2, 99)=74.58$, $p<0.001$). Again, the paired t-test that compared the separate selection strategies showed a significant difference between the intelligent tactic selection and the random tactic selection (t(99)=-11.11, p<0.001 and fixed tactic selection (t(99)=-12.10, p<0.001). These promising results show that a tactic selection based on the agent's situation awareness is effective.

6. Discussion

In this paper, a model for team decision making has been presented. The model has been inspired by various psychological theories (including those of Klein [8] and Endsley [2;3]) and consists of a number of components to come to judge the situation, derive a tactic and assign agents to the tasks that are part of the theory. As already indicated before, within the research in multi-agent systems, the combination of both models for situation awareness with more complex forms of team decision making has not been studied previously, whereas the importance thereof is highly emphasized by for instance Klein [8]. Within the domain of the case study, the model shows promising results.

Next steps for the research presented in this paper involve a more rigorous evaluation of the model itself. The main idea of this approach is to incorporate the model in a simulated opponent for fighter pilots that receive training in a flight simulator. The next step is then to evaluate the training value for these pilots, and investigate whether they consider the team decision making by their opponent's as intelligent.

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