Incorporating Global and Local Knowledge in Intentional Narrative Planning

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ABSTRACT

The inclusion of independent, imperfect knowledge that represents virtual agents' belief of the local state of a narrative planning world has become a key component of narrative generation through simulation of multiple characters. However such models of belief incur significant computational cost. This paper demonstrates that despite the computational complexity, narratives can be generated not only as emergent stories in simulations, but also by global search using Planning that includes a model of differing, independent beliefs. We define a narrative state suitable for planning, detail how it incorporates belief, and how this can be used in an intent-based global search based planning algorithm. Two example narratives are used to illustrate how imperfect belief and social actions can be used in the generation process. The planning algorithm, which integrates global narrative planning with local character level belief reasoning, is fully implemented in a prototype system which was used in the experimental evaluation in which narratives were generated against several objective functions with both global and greedy search. The results show that intent-based planning with belief modelling is able to: generate narratives beyond the reach of planners that have complete knowledge; and also efficiently produce objectively higher quality narratives than those generated by evaluation of only local character knowledge and beliefs.

1. INTRODUCTION

Interactive Storytelling (IS) systems feature virtual agents acting in accordance with system generated storylines, such as FAÇADE [14], FEARNOT [1], PROMWEEK [15] and FRIENDS [6]. AI planning has been widely used for generating narrative in IS and with the development of the IPOCL approach [19, 20] the importance of integrating *character intention* into planning based approaches has been highlighted (e.g. to ensure narrative quality with respect to audience perception of virtual agent believability [3] and story understanding [24]). Recent innovations in the area of intentional narrative generation have shown that the inherent complexity of this problem can be tackled via heuristic approaches and have managed to demonstrate intentional narrative generation within the time constraints imposed by real-time interactive environments [9, 23, 25].

However, these systems make an assumption of omniscience on the part of the plan generator and as a consequence there are a class of stories which they are unable to generate, namely, those stories which rely on the differing, possibly erroneous *beliefs* of different characters and the way in which these interact and can be manipulated as part of the plot. Examples of belief and its role in narrative abound, from Shakespearian classics such as *"Othello"* and *"Romeo and Juliet"* to folk tales including *"Little Red Riding Hood"*. Hence the motivation behind the work presented in this paper – to develop an efficient approach to intentional narrative generation which incorporates reasoning about character belief and enables the generation of narratives featuring such things as deception and manipulation.

Interestingly, and somewhat in contrast to work in the area of plot-based narrative generation, in simulation-based narrative generation the modelling of characters with imperfect beliefs is proving a fertile ground for increasing the potential for the emergence of interesting narratives [5, 21]. Typically a director agent or similar is included to drive the narrative toward author goals or preferences [13, 16]. However these directors make changes to characters' behaviours or decisions based on a local evaluation. The complex nature of the multi-agent simulations precludes the possibility for extensive search of the narrative space.

Our approach builds on the innovation introduced with the IMPRACTical approach of [23] and others such as GLAIVE [25] which achieve an efficient balance between planning at the *global* plot level with planning at the *local* virtual agent (or character) level by filtering actions deemed to be irrelevant in the context of characters intentions. We observed that such bi-level frameworks represented a suitable base for the addition of character belief since they already treat characters as separate virtual agents and hence we extended those approaches to support local reasoning about knowledge in the form of character beliefs. In our solution, this local reasoning is combined with global reasoning by an omniscient planner director which focuses on aspects of the narrative structure and ensures that the quality of the overall narrative is preserved.

The contribution of the work is the introduction of an efficient approach to the integration of a belief model for individual agents into a global optimizing intentional narrative planner. The integration of complete knowledge of the story world at the global level

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	Actor	Motivation	Action	Intent Effects
1.	-	-	fall-in-love Romeo Juliet	
2.	-	-	fall-in-love Juliet Romeo	
3.	-	-	decides-to-marry Romeo Juliet	**Adds:** Romeo intends married-to Romeo Juliet
4.	-	-	decides-to-marry Juliet Romeo	**Adds:** Juliet intends married-to Romeo Juliet
5.	Juliet	married-to Juliet Romeo	travel Juliet Capulet-residence Chapel	
6.	Juliet	married-to Juliet Romeo	borrow Juliet Lawrence Drug	
7.	Juliet	married-to Juliet Romeo	feign-death Juliet Drug	
8.	Romeo	married-to Romeo Juliet	travel Romeo Capulet-residence Chapel	
9.	-	-	grieve Romeo Juliet	
10.	-	-	decide-to-die Romeo	**Adds:** Romeo intends not alive Romeo
11.	Romeo	not alive Romeo	suicide Romeo Dagger	**Fulfils:** not alive Romeo
12.	Juliet	married-to Juliet Romeo	awaken-feign-death Juliet	
13.	-	-	grieve Juliet Romeo	
14.	-	-	decide-to-die Juliet	**Adds:** Juliet intends not alive Juliet
15.	Juliet	not alive Juliet	travel Juliet Market	
16.	Juliet	not alive Juliet	buy Juliet Apothecary Poison	
17.	Juliet	not alive Juliet	suicide-poison Juliet Poison	**Fulfils:** not alive Juliet

Figure 1: An example narrative generated containing 17 actions, for the author goals of Juliet and Romeo to be dead at the end of the narrative. Actions marked with actor "-" are happenings that can be added to a plan without a specific character's intent. All other actions are motivated on the basis of intent effects that have been added by other actions: for example, actions 15-17 are motivated by Juliets intention to die, which itself was added by action 14 (this intent also corresponds to 1 of the authored narrative goals). Refer to the text in section 3 for further detail.

(ie from the perspective of an omniscient director with a view to the overall plot) with incomplete, imperfect and differing models of belief and knowledge at the local level (ie from the perspective of the different virtual agents who populate a story world and who are driven by their own intentions which don't necessarily serve the overall goals of the narrative).

In the paper we include results of an experimental evaluation that support our hypothesis that, despite the increased complexity of reasoning about this kind of belief model, it can be incorporated into an efficient global optimising narrative generator. Measured against three objective functions, the results also show that the use of a global planner informed by local reasoning produces higher quality narratives than those produced using just local search alone.

2. RELATED WORK

With the development of the IPOCL approach to narrative generation [19,20], the importance of reasoning about character intention in planning based approaches was demonstrated for such aspects as virtual agent believability [3] and story understanding [24]. Since then this approach has been augmented to included other important narrative features such as surprise and suspense [2], adherence to author goals [18] and conflict [26]. However the aforementioned approaches are built on the use of partial-order causal link planning techniques [11] which have proved to be inefficient – when compared to some state-of-the-art planners which perform forward state-based search – with run-time performance that is unsuitable for real-time interactive applications of storytelling. As identified in [23] one cause of this is the inherent increase in the average branching factor that results from reasoning about intention.

Consequently, alternative approaches have been proposed which aim to tackle the efficiency problem in the generation of intentional narratives. For example, Haslum proposed a compilation of the intentional planning problem to a classical planning problem which can then be tackled by any state-of-the-art planner [9]. Nevertheless, as shown by Teutenberg et al [23], this compilation does not completely sidestep the additional overhead of reasoning about intention. The alternative approach they proposed with IMPRACTical [23] featured a bi-level generation technique which performed forward state-based search at both the level of the individual characters and the overarching plot thus enabling the identification of potential sources of co-operation between story characters and, for the domains they experimented with, providing an efficient way of generating intentional narratives. A similar approach features in the GLAIVE system [25] with reasoning at both the level of the narrative characters and the entire plot (via an "invisible puppet master"). Both approaches manage to reduce the average branching factor of the search by excluding actions which are deemed irrelevant, given the characters' current intentions. A key difference between IMPRACTical and GLAIVE lies in precisely how actions are classed as relevant. To determine relevance IMPRACTical performs an efficient restricted planning step for the characters concerned[1] whereas GLAIVE defers the decision and continues to search using *all* possible actions, only flagging actions as relevant if their motivating intent is reached at some later point in the search. We observe that the filtering of actions at the level of the individual narrative characters with IMPRACTical makes the approach very flexible and compatible with our aim of incorporating different models of knowledge and belief at the character level. Hence we have exploited this in the development of the approach we introduce here.

Another important aspect of generating narratives that feature believable characters relates to their individual knowledge of the world, in the form of each characters *beliefs* about the world, other characters in it and those characters motivations. A number of different story generation systems have incorporated reasoning about character belief. For example, the OZ [12] system featured characters with a sense-think-act perception system which allowed for the possibility of their world view being incorrect and provided opportunities for deception. Similarly, characters in THESPIAN [21] can have incorrect beliefs about aspects of the story world at different points in time. In the social planning approach of Chang et al [7] there was some reasoning about characters perceptions which enabled generation of stories featuring deception (illustrated with

[1]This is restricted in the sense that it uses a domain that has been "relaxed" i.e. facts that are deleted by actions are ignored [10].

	Actor	Motivation	Action	Intent Effects
1.	-	-	plan-cause-slay-loved Iago Othello Desdemona	**Adds:** Iago intends once-slew Othello Desdemona
2.	Iago	once-slew Othello Desdemona	order Iago Emilia	**Adds:** Emilia intends once-slew Othello Desdemona
4.	Emilia	once-slew Othello Desdemona	pick-pocket Emilia Desdemona Hankie	
6.	Emilia	once-slew Othello Desdemona	plant-evidence Emilia Cassio Desdemona Hankie	
7.	-	-	discover-infidelity Othello Desdemona Cassio Hankie	
8.	-	-	plan-cause-dead Othello Desdemona	**Adds:** Othello intends not alive Desdemona
9.	Othello	not alive Desdemona	slay Othello Desdemona	**Fulfils:** not alive Desdemona once-slew Othello Desdemona
10.	-	-	plan-cause-dead Othello Cassio	**Adds:** Othello intends not alive Cassio
12.	Othello	not alive Cassio	slay Othello Cassio	**Fulfils:** not alive Cassio
13.	-	-	grieve Othello Desdemona	

Figure 2: An Example Narrative for the Othello domain: illustrating the use of a social action by an agent, Iago, to cause intent in others, in this case that Othello will become jealous and plan to kill his wife (actions 6-8 where Othello's jealousy is triggered by the planting of evidence by Iago). The travel actions (#3, 5, 11) have been omitted for brevity. The author goals are for Desdemona and Cassio to both be slain and for Othello to be grieving. See text for further detail.

reference to Shakespeare's *Othello*). However this reasoning was restricted and relied on a single character having complete knowledge about other characters actions whilst the other actions could have incomplete and incorrect views of the world. More recently, an extension was introduced to the VST storytelling system [22] which enabled characters to perceive aspects of the world, form (possibly incorrect) beliefs on the basis of this and make assumptions about missing knowledge of the world.

With our approach we have integrated such a model of belief into an efficient intentional planning framework: as far as we aware the first approach to do so.

3. MOTIVATING NARRATIVE EXAMPLES

Before we outline our algorithmic approach in detail (Section 4), here we illustrate the application of belief in narrative generation via two examples that we use as illustration throughout the paper[2]. The first of these, from "Romeo and Juliet", has been selected to demonstrate how mis-informed characters can perform actions leading to the author goals that would not be reasonable with omniscient characters. The second example, from "Othello", demonstrates the use of social actions – in which an agent prepares a particular set of beliefs in another character so as to influence them in to gaining a particular new intent.

ROMEO and JULIET Example: Figure 1 illustrates the situation in an encoding of Romeo and Juliet where agents are confused by their incorrect beliefs while planning to marry. Instead, once at the Chapel, Romeo believes Juliet is dead (not realising she is able to awaken from her feigned death) and proceeds to commit suicide. Juliet, unaware of this, awakens from her slumber and does the same. This plan has been generated using our implemented narrative generator which we describe in full in Section 4. Below we outline the way in which the characters' beliefs give rise to the plan shown in Figure 1 (numbers correspond to action index in the plan).

5. Juliet doesn't know Romeo shares her intent to marry. She relies on the probable happening of Romeo desiring to marry her, treating it as an axiom.
7. Juliet expects Capulet to grieve her death, thereby breaking the bond requiring his permission to marry.
8. Romeo knows nothing that occurred in the Chapel but does assume Juliet has fallen in love with him, so he continues working toward marrying her.
9. Romeo perceives that Juliet is not alive, but not that she is feigning death.
11. As Juliet is not conscious she does not perceive the action of Romeo committing suicide.
12. Only after the act of waking is completed will Juliet realise her intent can no longer be reached.

OTHELLO Example: The second example in Figure 2 roughly corresponds to the Othello example of Chang and Soo [7]. In this case Iago and Emilia make use of social actions by planning to cause a situation in which Othello intends to slay his own wife Desdemona.

6. Adds a deceptive fact that Desdemona gave Cassio the handkerchief.
7. This sets up the social action: it is considered probable that Othello will draw the infidelity conclusion
8. .. and it follows that it is probable that he will take revenge by killing Desdemona.
12. An unexpected side-affect of Iago and Emilia's plan. Now Othello also intends to slay Cassio. This has no relation to Iago's intents but will address an author goal.

4. INTEGRATING BELIEF INTO INTENTIONAL NARRATIVE

We have developed a forward state-based approach to narrative generation that integrates reasoning about beliefs and intentions at the local character level with global reasoning about the overall structure of the plan. Parts of the algorithmic approach we have developed builds on that introduced by Teutenberg et al in [23] and for brevity in this section when the algorithmic aspects are essentially unchanged we omit detail and refer the reader to their work.

[2]Planning models of both these domains, encoded using PDDL (augmented with additional information for belief handling), are available to download from `https://www.scm.tees.ac.uk/j.porteous/AAMAS-2015-domain.zip`

4.1 Representational Framework

We adopt a representational framework in which the structure of a narrative generation domain and problem are defined as tuples $\langle F, O, A \rangle$ and $\langle S_I, S_G \rangle$ of possible facts, actions, characters, initial facts and authored goal facts respectively. The actions are STRIPS-based [8] with preconditions, add and delete effects each being subsets of F and additionally are associated with an actor $actor(a) \in A$.

Note that in the paper we distinguish between characters, actors and (planning) agents as follows: a *character* is a type of object in the world (a type in the PDDL sense); an *actor* is a character that performs an action; and a (planning) agent operators at the local individual character level generating plans and reasoning about relevant actions for a particular character.

An intent-based world state contains not only a set of facts that are currently true, but also a set of intents I made up of character-goal pairs $\langle a \in A, f \in F \rangle$.

To encompass character beliefs additional sets of facts are included in the world state as follows: in addition to the current true facts $S \subseteq F$, we include a set of belief facts for each character $a \in A$, denoted $S_a \subseteq F$ and belief intents I_a. As agents' plans rely on cooperation and prediction of others' future actions, a model must also address the potentially recursive belief of others' beliefs. We adopt the following solution to this: include in the model a final set of facts S_P representing "popular belief" – what an otherwise uninformed member of the population is expected to know about the world state. Whenever an agent reasons about another agent's belief, they assume the other agent is operating from the popular belief. So in total, for a problem with n characters there are $n + 2$ sets of facts contained in a world state, thus providing a practical solution to this problem.

4.1.1 Model of Belief

Finally, the narrative domain requires some device by which characters' beliefs can be changed and made to differ from reality and that of other characters. In general, this can be a set of context sensitive effects on each action, adding and removing facts from each of the characters' belief sets. For agents' prediction of expected future events to remain reliable, these effects should not differ drastically from the standard effects that are applied to the current state. Conversely, perception must differ from the standard effects often enough to enable interesting interactions within a narrative.

While the planning procedure we introduce in this paper represents a general approach which is largely independent of the specifics of the perceptual model, there is still a requirement for human domain authors to provide sufficient flexibility (through actions) for the planner to be able to manipulate the characters' beliefs. In section 4.3 we discuss the process of authoring actions in order to provide this functionality with aspects such as deception and social influence.

For the purposes of the experimental evaluation in Section 5 we detail the perceptual model which we have used in our experiments (an alternative would, for example, have been to use another function such as that from the model in Hide and Sneak [22]).

The perceptual model used in this evaluation modifies beliefs based on the world state, the action being applied, a set of predicates designated as perceivable properties; location and character objects; and the special predicates *conscious* and *at-location*. Actions are augmented with a set of participant characters, and are designated as private or public based on their schema and the location in which they occur (if any).

The following set of rules are applied with each action:

procedure RELEVANT-BELIEF($S_P, I_P, S_0..S_{n-1}, I_0..I_{n-1}$)
2: $R \leftarrow$ RELEVANTACTIONS-PREDICT$(()S_P, I_P)$
for $i \in \mathbb{Z}_n$ **do**
4: $O_i \leftarrow O_i \cup R \cup O_{prob}$ ▷ Update available actions
end for
6: $R \leftarrow \emptyset$
for $i \in \mathbb{Z}_n$ **do**
8: $R_i \leftarrow$ RELEVANTACTIONS-PREDICT(S_i, I_i)
$R \leftarrow R \cup (R_i \cap O_i)$ ▷ Store the ith agent's relevant
10: **end for**
return R
12: **end procedure**

Figure 3: Outline Algorithm for predicting Relevant Actions with Local Character Belief: S_P and I_P are beliefs and intents from the popular belief set; I_i and S_i for $i = 0 \ldots n-1$ are the fact and intent belief sets for the n characters in the domain. The function RELEVANTACTIONS-PREDICT is taken from [23] and here used for calculating relevant actions for characters with different possibly erroneous beliefs about the domain. In line 2 the set of relevant actions are predicted for intent and belief sets taken from the set of popular beliefs. In line 8 the set of relevant actions are predicted for each of the characters taken into consideration their individual intents and beliefs.

- Characters who are not *conscious* do not change belief.
- If an action changes an object's location, all agents at its previous and new location perceive predicates relating to this object.
- If an action is public, all agents and the popular belief perceive moved objects' predicates.
- If an action changes a character's location, that character perceives the predicates relating to all objects at its new location.
- The actor and all participants of an action perceive its preconditions and effects.
- If an action is public, all agents and the popular belief perceive its preconditions and effects.
- When an action commands another character, all beliefs of the commander are passed to the commandee. This ensures their collaboration will produce mutually compatible plans.

4.2 Identifying Relevant Actions with Belief

In our approach narratives are generated by a global planner which plans forward using a state-based search. As with the approach of [23] we use local reasoning at each state that is visited to filter the action set so that the global planner can use just those actions that are relevant given the current state of the world. In our work we have extended this mechanism to incorporate character beliefs.

For each state that is visited during the global search, an action is deemed to be relevant in that state when two conditions are met. Firstly, if its preconditions are a subset of the current state's facts and secondly, if the character's agent considers it relevant (e.g. given the current intents and goals for that character).

We adopt the first condition where actions' preconditions must be a subset of the actual world state (it is conceivable that a domain could be authored with actions that have preconditions over both beliefs and 'reality', yet as demonstrated in the examples in Section 3, this additional complexity is not required to achieve features such as deceit in narratives).

It is with respect to the second condition that we deviate from [23] since relevant action reasoning must include consideration of character beliefs. An outline of the algorithm for the construction of this set of actions is shown in Fig. 3 and involves running the relevant action algorithm from [23] multiple times for the planning agents associated with each character over different belief types:

1. Relevant Actions from Character Beliefs: this run identifies the set of relevant actions for a character given its set of beliefs in the current state.
2. Relevant Actions from other Characters Beliefs (i.e. Popular Belief): A single run, as described in [23], using S_P gives the set of relevant actions for each agent *as expected according to popular belief*. For any given agent, this is the set of actions they believe all other agents will try to make use of. Thus these predicted future actions can be used by any agent when constructing their individual plans, so long as their preconditions are met.
3. Relevant Actions from Happenings: Agents can make use of some happenings (actions that require no actor) that are declared 'probable' O_{prob}. These are treated as axioms, though as the agents reason with relaxed versions of planning domain models (relaxed in the sense that delete lists of actions are ignored) these do not threaten causal links and can only ever increase the set of reachable actions. An example of a probable happening is:

Action:	**catch-cold ?a - char ?p - location**
Precondition:	(at-location ?a ?p)
	(raining ?p)
Effect:	(sick ?a)

and, to contrast, a happening only considered possible is:

Action:	**lightning-strike ?a - char ?p - location**
Precondition:	(at-location ?a ?p)
	(raining ?p)
Effect:	(not (alive ?a))

An agent treats *catch-cold* as an axiom and so if it intends to make someone *sick* its plan only needs to achieve the appropriate *at-location* fact while *raining* is true. However the global planner treats this as any other happening, so a character will actually only become sick if it serves the purpose of the narrative. The lightning-strike action is never used by agents when determining their relevant actions, but if a character were to end up in the rain the global planner could choose to make use of this. The possible actions have an important role in providing additional options to the global planner, but the probable actions also form the basis for enabling social actions and influencing other agents. This will be discussed further in Section 5.

Hence we deviate from earlier approaches, where identification of relevant actions for a character relied solely on that character's own actions, and expand the set of relevant actions to include the following actions: the combined set of actions that a character is an actor for, and the predicted relevant actions based on popular beliefs of all characters, and the probable happenings which are then integrated in to the relevant action process using an implementation of the g function of [23] which determines reachable actions from a given state. This expanded set of relevant actions enables the generation of narratives that feature deception and social influence (this is demonstrated in the evaluation in Section 5).

Overall the algorithm for relevant action identification, as shown in Fig 3, requires $n + 1$ calls to an implementation of the function RELEVANTACTIONS-PREDICT [23]: one for the popular belief used to model each agent's prediction of others beliefs, and one for each agent from their own beliefs.

4.3 Authoring Deceptive and Social Actions

The model of belief and the algorithm of Figure 3 describe how to determine which actions an agent will believe it can make use of based on prediction and cooperation. However, this alone is insufficient to enable the generation of narratives that are not possible with omniscient characters. In this section we give examples of action effect and precondition facts that, when combined with the relevant action algorithm, can produce new interactions with deception and social actions. We also introduce some limited requirements for a perceptual function p that ensure these actions are able to effectively deceive characters.

In authoring a deceptive effect for an action, we pair a 'fake' effect with one that flags it as being deceptive. The first fact of the pair x_1 should be perceptible, i.e. when it is an effect of an action it will be added by the perceptual model function for all characters. The second fact x_2 should not be perceived by at least some characters. Other actions that rely on x_1 as a precondition have *not* x_2 added as a requirement. Those agents that do not perceive x_2 will then erroneously make use of these actions in their planning. As illustration an action involving deception that features in our Romeo and Juliet example is as follows:

Action:	**feign-death ?a - char ?d**
Precondition:	(has ?a ?d)
	(potion ?d)
Effect:	(not (alive ?a))
	(feigning-death ?a)
	(not (has ?a ?d))
	(not (conscious ?a))

Here x_1 is *not alive* and x_2 is *feigning-death* indicating that this effect is deceptive. Other actions that make use of the *not alive* fact can be modified so that they are not used if the deception is known, by adding *not feigning-death* as a precondition. Finally, a second action that removes the deception is added

Action:	**awaken-feign-death ?a - char**
Precondition:	(feigning-death ?a)
Effect:	(alive ?a)
	(not (feigning-death ?a))
	(conscious ?a)

In the Romeo and Juliet example, Juliet plans to make use of this action pair so that by feigning death she can have Capulet no longer be her legal guardian (a precondition for one method of achieving her goal to marry Romeo). However, the narrative planner was also able to make use of this and have Romeo believe he was unable to marry Juliet, to grieve, and then to decide to commit suicide.

Our second example problem, Othello, provides an example of social actions. A social action is one in which an agent prepares a particular set of facts that will cause another character to gain a new intent. Our approach is to model these as probable happenings like the example *catch-cold* discussed earlier in Section 4.2, but with additional effects on agent intents. In the Othello example the key social action is *plan-cause-dead* in which an intent to have another character *not alive* is added given the precondition that they have *negative-affinity*. The other half of the social action is then planning to achieve *negative-affinity* which could in theory be performed by

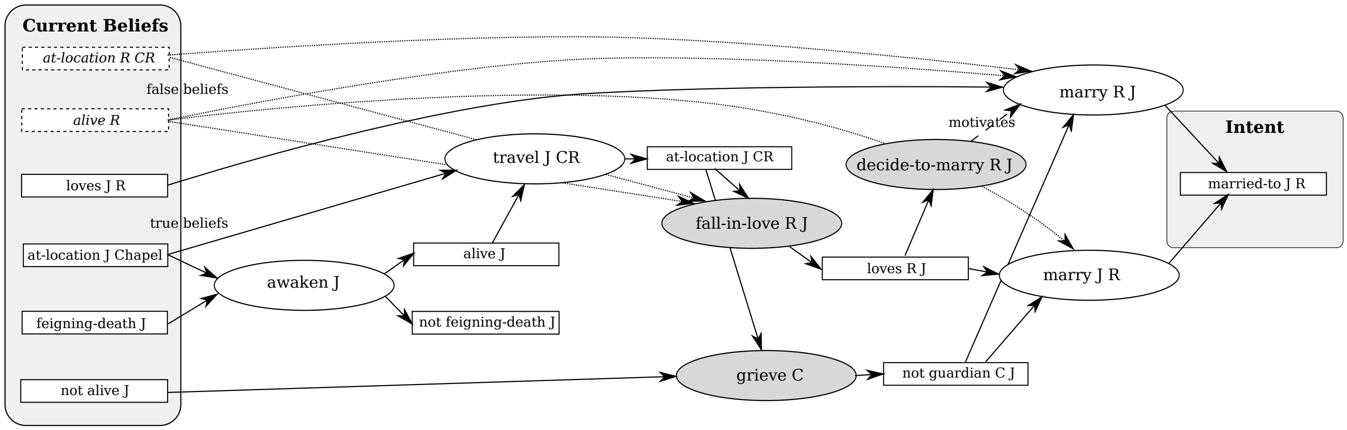

Figure 4: Relevant Action Reasoning for Juliet. The figure shows the relevant actions for Juliet with the current state that she is feigning death and her current belief set includes the erroneous beliefs that Romeo is still alive and at the Capulet residence (in reality he is dead at the chapel). The graph shows the relevant actions that make up the possible relaxed plans for Juliet based on partially incorrect belief, just before waking. The plans are relaxed in the sense that delete effects of the actions are ignore. Facts are shown in rectangles. Actions are shown in ovals with shaded actions indicating probable happenings. See text for further detail.

several different actions. In the Othello problem the key enabling action is

Action:	**discover-infidelity ?a ?b ?c - char ?o**
Precondition:	(once-gave ?b ?c ?o)
	(values ?b ?o vast)
	(married-to ?b ?a)
Effect:	(negative-affinity ?a ?b vast)
	(negative-affinity ?a ?c vast)

This action is in turn enabled by the deceptive action of planting evidence of the handkerchief, forming the core of the plot.

4.4 Example Deceived Agent's Plan

We conclude this description of our method for intent-based planning with belief with an example of an agent's relevant actions that represent their possible intended plans. For the Romeo and Juliet example, Figure 4 shows the full set of relevant actions, both those from the popular belief and those originally available to Juliet, just prior to her awakening from her feigned death. The delete-relaxed actions are partially ordered according to the causal links between action effects and later actions' preconditions.

On the left of the figure are the pertinent facts in Juliet's belief set at the current node of the search space for the global narrative planner. Two of these are not true – she believes that Romeo is still at the Capulet residence and is still alive, whereas in reality he is at the Chapel and is no longer alive. Without these two facts no valid sequence of actions would exist leading to the target intent *married-to Juliet Romeo* shown on the right.

This graph of actions was constructed using an implementation based on [23] expanding forward from the initial state (in this case, Juliet's beliefs). Once her target intent was reached, it backtracked through the graph following causal links to obtain the set of relevant actions. All relevant actions are shown in the figure. In this case, the set of relevant actions represents two possible plans: one relying on Romeo falling in love with Juliet so she can marry him; the other further expects Romeo to intend to marry Juliet and later performing that action himself. In both cases the bond between Capulet and Juliet must be broken through her deception that will cause Capulet to grieve her death.

The key point here is that our inclusion of beliefs is essential in order to be able to identify these relevant actions. Without the reasoning about belief that our approach provides Juliet's initial state could not contain false beliefs and would have resulted in her having no relevant actions. If imperfect beliefs were added without the inclusion of the probable happenings, Juliet would never believe that Romeo could love her and again could not plan to reach her intent and would have no relevant actions. Only by combining these two features is she able to both be deceived by incomplete knowledge, and bridge the gap in her knowledge through the prediction of probable events, thereby completing her anticipated plan through to her goals.

4.5 Global Narrative Generation with Belief

Using the approach introduced in [23], our implementation generates global narratives via A* forward search in the manner of HSP [4] with the set of actions considered restricted to those identified using RELEVANT-BELIEF (as outlined in Fig. 3) at each search node. This implementation was used to generate the example narratives discussed earlier (Figures 1 and 2) with efficient performance (consistent with that reported in [23]) resulting from the reduction in average branching factor due to action relevance filtering.

5. EVALUATION

The evaluation of our belief-based extension to intentional planning that we introduce in this paper has two aims. Firstly to show that it is capable of producing types of narratives impossible in approaches that do not reason about character belief: narratives that feature deception based on imperfect and differing character beliefs and narratives generated by planning agents that can utilise social actions which influence other characters' intents. Secondly, to demonstrate that when modelling belief for each character an intent-based planner produces higher quality narratives than a narrative guided by greedy local evaluation of beliefs.

In order to evaluate these aims we have implemented the system described, and constructed a model of belief which would ensure that characters' beliefs diverge from reality during plan execution (as described earlier in section 4.1.1). Narrative domains describing the predicates and action schema have been constructed for our two example domains of *Romeo and Juliet* and *Othello*[3], using PDDL augmented with features to handle the model of belief.

5.1 Narratives with Deception and Influence

Our implemented system was used to generate narratives for the *Romeo and Juliet* domain and for the *Othello* domain. They exhibited the following features:

- The Romeo and Juliet narratives shown in figures 1 and 4 illustrates the confusion that can arise as a consequence of erroneous beliefs.
- The Othello example shown in figure 2 illustrates the use of social influence in a plan where one character successfully manipulates the situation to result in a change in another characters beliefs and their intentions.

This illustrates how the inclusion of belief reasoning enables the generation of narratives that incorporate social actions and deception. Importantly, narratives such as these would be impossible to generate using approaches such as IMPRACTical [23] or GLAIVE [25] since they assume complete knowledge on the part of all agents.

However the converse is true: our extended belief based approach is still able to generate narratives where characters do not have beliefs i.e. all agents have complete knowledge of the world and all other characters intentions (e.g. as described in [20, 23]). This is achieved in our approach by assigning all agents full, correct belief in the initial state and then using the perceptual function to assign the current state to each character's belief every time an action is performed (i.e. thus rendering the characters omniscient).

5.2 Experiments to Assess Narrative Quality

To compare the quality of narratives generated using a global approach that reasons about character beliefs with a greedy search we have implemented a selection of three objective functions to be optimised in addition to achieving the authored goals for each problem. We use the same metric function and heuristic for both forms of search so that there is no difference in information available to each. In comparison to our implemented approach, a greedy hill-climber over the heuristic values is used as an approximation of a director-led narrative with multiple character agents.

Note that we make no claims as to how the values of these functions relate to subjective plan quality, only that they present a variety of fitness landscapes for the search to explore and that we have attempted to select functions that have some relation to properties that have been identified as useful or interesting in narrative planning. The experiment is designed under the assumption that, while non-trivial, it is possible to construct an appropriate metric function for a given problem that correlates with an author's view of resulting narrative quality.

- **Minimum Length**: the first objective function we use in this evaluation is the same as that used by IPOCL, IMPRACTical, and GLAIVE: to minimise the number of actions in a narrative while reaching all author goals. As a metric function this represents the desire for a compact narrative without superfluous actions or padding of the plot. Evaluating this function was performed with a single run of each approach (greedy and a-star based planning) on the two example problems.
- **Minimum Cost**: the second objective function minimises total plan cost. Each action has an integer cost associated, and the cost of a plan is the sum of its component actions' costs. Such a metric could be used when an author prefers some actions over others, where assigning a high cost provides an incentive to search for alternative plans. Evaluating this metric was performed by ten assignments of random values between 1 and 100 to the costs of ground actions. Each assignment was then used with both greedy and global search.
- **Target Cost**: the third metric is for plan cost to be as close as possible to a target value. Such a metric may be useful when producing narratives for authoring systems that define narrative trajectory as sub-problems between landmarks [17]. Here action cost could be presentation time, in which case this metric can manage the rate at which landmark beats are reached. Alternatively, cost could be a measure of inherent tension in an action, in which case the sub-plans' target costs will depend on the authored arc for that part of the narrative. Evaluation was performed in the same manner as for the minimum cost, with 10 repeats of random assignment of costs to ground actions. The target cost in all cases was set to 1000; around two to three times the average minimum cost for the Romeo and Juliet problem and around four times the average minimum cost for the Othello problem.

[3]Available on-line from: https://www.scm.tees.ac.uk/j.porteous/AAMAS-2015-domain.zip

		Planner Quality		Greedy Quality	
Metric	Problem	Mean	S.D.	Mean	S.D.
Min Length	Othello	9	-	9	-
Min Length	R/Juliet	11	-	20	-
Min Cost	Othello	315	59	389	113
Min Cost	R/Juliet	473	98	491	96
Target Cost	Othello	3.5	0.2	-	-
Target Cost	R/Juliet	0.2	0.4	47	65

Table 1: Narrative quality measured using the metrics Min. Length, Min. Cost and Target Cost applied to narrative generation using Global and Greedy search of the narrative space (labelled Planner Quality and Greedy Quality respectively). Note that the generation with greedy search in the Othello domain often led to narratives that could not be extended to reach the author goals, denoted using '-'. See text for further detail.

5.3 Results: Narrative Quality Experiments

Table 1 shows the resulting plan quality according to each of the three metrics tested. For the minimum length metric the results are deterministic, so a single run was used giving no standard deviation for the results. For minimum and target cost, the standard deviation is calculated over the ten repeats for each table row. In all cases the global planner's quality is statistically significantly higher than that of the greedy search using local heuristic estimates. This is the expected result as the heuristics are usually admissible meaning the a-star search will consider the greedy result in addition to other parts of the narrative space.

The Othello problem is the shorter of the two used and has fewer narrative options for reaching the author goals. For the minimum length, the heuristic was sufficiently informative that a greedy ascent found the same optimal solution as the global planner. When working toward a target cost the limited options often caused the greedy search to reach a point in the narrative space in which the author goals became unreachable.

The quality values for minimum length and minimum cost are both given as total values for the plan, so lower is better. The target cost value is the absolute difference between the total cost of the plan and the target value. Again, lower is better. There is a sufficient range of options and action values that narratives can be generated that closely match the target cost. This is a positive result for the approach when used with such an objective function, but does lead to much lower values than the other two metrics.

For the Romeo and Juliet problem global intent-based planning produced a narrative 1.8 times closer to the minimum length than the greedy hill-climbing using local heuristic evaluation. This may be an outlier in terms of the difference between the two approaches, as when costs were randomised the improvement averaged only 1.03 times. Regardless, the narratives are statistically significantly better and with more elaborate problems in larger worlds we expect these values to diverge further. When optimising to a total narrative cost to a target value, the difference was more marked. Here the global search found an optimal solution with the exact target cost in most cases, making it hundreds of times closer to the target value on average.

6. CONCLUSION

We have shown that models of belief can be incorporated in to intent-based global planners and that this makes it possible to generate narratives otherwise unobtainable using existing omniscient characters. Two short but non-trivial illustrative examples have been presented that are produced by an implementation of an algorithm designed to operate on the extended model of belief. This demonstrates how even a limited modification to relaxed agent's planning, coupled with careful authoring of action schema can produce narratives with deceit and social interaction.

Our implementation has been evaluated against a baseline using a 'director' agent that utilises the same heuristic knowledge as our planner but in local evaluation only. For three metrics associated with narrative properties identified in the literature, the global planner has been shown to produce statistically significantly higher valued narratives than its local-evaluation counterpart.

The results demonstrate that efficient generation of narratives that meet global metric criteria, and the modelling of individual character belief, need not be mutually exclusive.

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