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Adapting Game-Playing Agents to Game Requirements

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Abstract

We examine the problem of self-adaptation in game-playing agents as the game requirements evolve incrementally. The goal of our current work is to develop an interactive environment in which the game designer generates requirements for a new version of a game, and the legacy software agents from previous versions of the game adapt themselves to the new game requirements. We are developing and testing our metareasoning technique for adapting a game-playing agents in Freeciv, a mature program in the domain of turn-based, multi-player strategy games. In this paper, we first present an analysis of adaptations to FreeCiv, next describe our general approach, and then describe a specific adaptation scenario.

Introduction

Designs of long-living interactive games evolve through many versions. Changes from one version of a game to the next typically are incremental and often very small. A game designer (or a team of game designers and software engineers) formulates the requirements of the new version of the game, adapts the software for playing the previous versions to meet the new requirements, and implements and evaluates the modified designs of the game and the software. Typically the game designer uses high-level scripting languages to define the game environment (percepts, actions, rules, constraints) as well as the behaviors of various virtual agents in the game. We posit that an interesting research issue in game playing is how might a virtual agent adapt its design, and thus its behaviors, to very small changes in its game environment. If the changes in the game environment can be arbitrarily large and complex then this becomes an "AI-complete problem." However, even if the changes to the game environment are incremental and very small, this is a hard computational problem because changes to the environment can be of many types, modifications to the agent design can be of many types, there is no one-to-one mapping between changes to the environment and modifications to the agent design, and any modification to the agent design needs to be propagated down to the level of program code so that the new software is directly executable in the game environment.

Genetic programming clearly is one computational technique for addressing this problem. However, for complex game-playing agents, the space that must be searched by genetic algorithms can be prohibitively large. In order to manage this complexity, we have taken a knowledge-based, deliberative approach to agent redesign. In previous work, we have investigated the use of metareasoning for self-adaptation in software agents, which may offer an effective technique for adapting virtual agents in game playing. It is useful to make a few distinctions here. Firstly, adaptations to an agent can be retrospective (i.e., when the agent fails to achieve a goal in its given environment; (Genesereth 1983) (Birnbaum et al. 1990) (Stroulia and Goel 1995) (Leake 1996) (Murdock and Goel 2001), or proactive (i.e., when the agent is asked to operate in a new task environment; e.g., (Murdock and Goel 2003) (Murdock and Goel 2008). Secondly, adaptations can be either to the deliberative element in the agent architecture (Genesereth 1983) (Birnbaum et al. 1990) (Stroulia and Goel 1995) (Leake 1996) (Murdock and Goel 2008), or the reactive element (Stroulia and Goel 1999), or both. Thirdly, adaptations to the deliberative element may be modifications to its reasoning process (i.e., to its task structure, selection of methods, or control of reasoning; e.g., (Birnbaum et al. 1990) (Stroulia and Goel 1995) (Leake 1996) (Murdock and Goel 2008)), or to its domain knowledge (i.e., the content, representation and organization of its knowledge; e.g., (Jones and Goel 2009)), or both.

In this paper, we examine the use of teleological metareasoning for proactive adaptation of an agent's deliberative processing, specifically in the context of game-playing software agents. Our work in this area investigates the hypothesis that a declarative self-model that captures the teleology of the agent's design may enable localization, if not also identification of the elements in the reasoning process responsible for a given behavior. The basic theme of our work on metareasoning for self-adaptation in intelligent agents has been that *teleology is a central organizing principle of knowledge representations that enable self-adaptation of reasoning processes.* This work uses teleological self-models to allow the metareasoning process to perform self-diagnosis. Having done this, the metareasoning process can then perform self-adaptation at the identified location(s). The goal of the work described here is to develop an interactive environment called GAIA (for Game Agent Interactive

Adaptation) in which the game designer generates requirements for a new version of a game, and the legacy agents from previous versions of the game adapt themselves to the new game requirements in cooperation with the human designer, who provides guidance where automation is not possible or not implemented. We are developing and testing our metareasoning technique for adapting a mature program in the domain of turn-based, multi-player, strategy games, specifically FreeCiv (www.freeciv.wikia.com). In this paper, we first present an analysis of adaptations to FreeCiv, next describe our general approach, then describe a specific adaptation scenario, and finally discuss our plans for future work.

Architecture for Adaptation

We have taken a teleological approach to software adaptation, addressing the problem of adapting software by connecting a teleological model to the source code. The teleological model is expressed in a language we have devised called TMKL (Murdock and Goel 2008). Further, we have built a development environment called GAIA to automate the adaptation process. GAIA has two interesting features that we describe: its reasoning engine, REMng, and its code generation mechanism.

GAIA

GAIA is an interactive development environment, implemented in Eclipse (http://www.eclipse.org/) that supports a modeler in building TMKL models and then using them to adapt the modeled software. Its architecture is depicted in Figure 1.

The user-facing portion of GAIA is called SAGi, which appears in the center of the diagram. Besides providing overall control of the adaptation process, it supports users in building TMKL models. To the right of SAGi is a module responsible for managing TMKL models and persisting them. Persistence is currently provided via Eclipse's EMF package. The other two parts of GAIA are its inference engine, REMng (at the top of the diagram), and its code generation mechanism (under SAGi). The code-generation mechanism is based on a domain specific language (DSL) that provides a means of expressing objects and relations that exist within the game domain. We intend to support the addition of off-the-shelf machine learning tools, such as planners and learners, via an interface to REMng. To the left of SAGi in the figure is an event log for communicating run-time information back to REMng.

TMKL

TMKL is a teleological modeling language intended to support automated reasoning about software systems (Murdock and Goel 2008). The name is an abbreviation for Task-Method-Knowledge Language. *Tasks* in TMKL express a system's goals in terms of inputs and outputs. *Methods* describe the mechanisms by which a system accomplishes its goals. *Knowledge* comprises the application-domain concepts and relations on which the system operates.

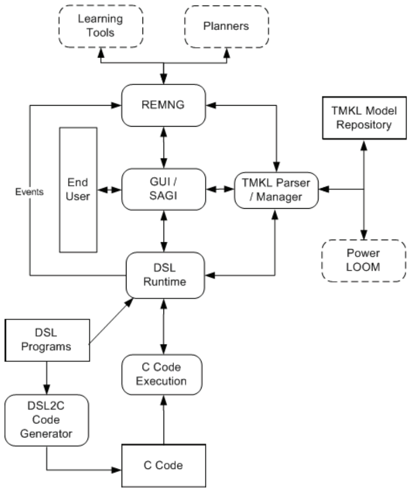


Figure 1: GAIA Architecture

Tasks and Methods are defined in alternating hierarchical layers. The topmost Tasks describe a system's ultimate goals as black-box functional specifications. Each Task is implemented by any one of a set of alternative Methods, which it superordinates. Methods, in turn, organize the operation of a set of sub-Tasks. At the bottom of the hierarchy are primitive Tasks, available as executable units of code.

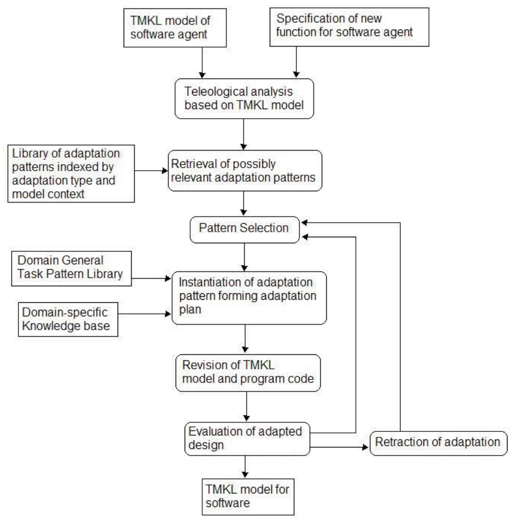
TMKL Tasks are defined by five pieces of information: input Knowledge elements, output Knowledge elements, required input conditions (pre-conditions), produced output conditions (post-conditions), and implementing Methods. Methods are defined similarly in terms of their preconditions, sub-Tasks and ordering constraints, represented by finite state machines. Finally, Knowledge in TMKL is defined in terms of application-domain concepts and their relationships. An example of TMKL is depicted in Figure 3, and discussed below in the section describing our case study.

REMng

GAIA's inferencing mechanism is called REMng. REMng works in conjunction with the code generation mechanism described in the next subsection. That is, REMng, when given a program model expressed in TMKL and an adaptation goal, produces an adapted model as output. The model is then used to generate new code implementing the adapted model.

Figure 2 illustrates the process for software adaptation implemented by REMng. The process begins with a specification of program goals and their connections to the program code, represented via a TMKL model, and a specification of the differences between the goals delivered by and desired of the software. REMng uses the TMKL model, localizes the needed modifications in the model and identifies adaptation patterns corresponding to the needed modifications. The application of each retrieved adaptation pattern is localized to specific components.

Adaptation patterns have two parts: rules for determining the applicability of the pattern in a particular problem



TMKL model of software agent
Specification of new function for software agent
Teleological analysis based on TMKL model
Library of adaptation patterns indexed by adaptation type and model context
Retrieval of possibly relevant adaptation patterns
Pattern Selection
Domain General Task Pattern Library
Instantiation of adaptation pattern forming adaptation plan
Domain-specific Knowledge base
Revision of TMKL model and program code
Evaluation of adapted design
Retraction of adaptation
TMKL model for software

Figure 2: REMng's process for adaptive software design

context and procedures for changing model elements to effect the adaptation. Each adaptation pattern is parameterized according to the specifics of the requirement change that caused its retrieval as well as the local context in which it is being applied. This parameterization step results in a fully instantiated and executable set of *adaptation plans*. The parameterization process of an adaptation pattern, for example, may try to find a replacement for a primitive Task in the TMKL model. If such a primitive Task is not available in a component library, the pattern may be rejected and REMng may instead try to parameterize a different retrieved adaptation pattern that abstracts the adaptation goal. If such an abstract primitive Task is available in the pattern library, REMng is able to parameterize the adaptation pattern to form an adaptation plan, which in turn would instantiate the corresponding abstract primitive Task and the specific portion of the program code it points to and adjust them accordingly.

The adaptation is completed by iteratively executing the adaptation plans that were successfully instantiated and asking the user to confirm or reject each change. The TMKL model is correspondingly revised by propagating the effects of the changes to the original model, and the revised model is passed to the code generation component for translation into an executable form. An example of REMng's processing of an adaptation request is presented below in a section describing our case study.

Generating program code

The primary purpose of the code generation component of GAIA is to provide a mechanism for realizing the effects of adaptations during program execution. A secondary purpose is to provide infrastructure for abstracting away programming-language and implementation-specific details from TMKL models. As a result, models and explanations of purpose can be expressed in a domain-specific manner, and the process of reasoning and adapting TMKL models can take place at a high level of abstraction.

Code generation consists of four phases. The first phase converts the TMKL elements into a type- checked semantic model. In the second phase, the elements of the model are translated into an abstract syntax tree (AST) representation. Nodes in the tree correspond to grammatical constructs in the target programming language. At this point, constraints from the game environment and programming language are absent from the model. Run-time details relevant to the execution of the model, but not necessarily its semantics, must now be reintroduced. Examples include dynamic allocation and freeing of game resources, safe storage and retrieval of game objects, iteration over game objects or how a domain concept in the knowledge base is actually mapped into run-time elements in the game environment. To introduce these concerns, the third phase traverses the AST of the model and expands any domain concepts or operators with the necessary constraints. Also during this phase, probes for producing feedback events to be sent to REMng are inserted into the AST. This feedback will allow REMng to determine whether failure to achieve goals expressed in the TMKL model has occurred, and, if so, to start a retrospective adaptation process. However, this retrospective adaptation is not yet implemented. Finally, the fourth phase takes in the completely augmented AST translated from the original TMKL model and emits pretty printed code files. Using SAGi, the user can then request that the resulting code be compiled, linked and run.

Case Study

We have studied the teleological approach to software adaptation by applying it to a specific adaptation scenario for the FreeCiv game. To illustrate the approach, we first describe FreeCiv and then the scenario. We then evaluate the approach in the following section.

FreeCiv

FreeCiv is an open source variant of a class of Civilization games with similar properties. The aim in these games is to build an empire in a competitive environment. The major tasks in this endeavor are exploration of the randomly initialized game environment, resource allocation and development, and warfare that may at times be either offensive or defensive in nature. Winning the game is achieved most directly by destroying the civilizations of all opponents, but can also be achieved through more peaceful means by building a civilization with superior non-military characteristics, such as scientific development.

FreeCiv is written in the C programming language and includes 157K lines of source code. One component of the game is an AI game-playing agent used when not enough human players have joined the game. The AI agent that is the target of our adaptation experiment comprises 20K lines of code.

FreeCiv adaptation scenario

A typical strategy undertaken by the FreeCiv AI agent is to grow cities until they are big enough to support advanced technology research. However, a problem with large cities is that citizens can become dissatisfied (unhappy).

In our experiment, we changed the rules of FreeCiv. We added a new rule involving luxury items. Luxuries are special resources that may be randomly found on the FreeCiv game map. The added rule states that if a player's city is connected to a luxury item by a road, the *happiness* value of citizens of that city is increased. The happiness value of a city has secondary impacts, including an effect on population growth of the city. After applying the adaptations described in the following section and generating code for the adapted agent, we can see that the adapted agent does in fact exploit this new rule by building roads that connect its cities to luxury resources.

REMng

In the luxury adaptation scenario, REMng works with the TMKL model depicted in Figure 3, without any of the portions contained within the three bold-outlined boxes. The portions within these boxes were added by REMng during the adaptation process, resulting in a new, adapted agent that is able to exploit the new game rule that is added in this adaptation scenario. In the figure, the containing, named rectangles are TMKL Methods. The contained, unlabeled rectangles are Tasks. The lines between Tasks in the Methods depict control flow (state transitions) while the lines from Tasks to Methods illustrate which Methods implement particular Tasks. This figure depicts the "Largepox" strategy for playing FreeCiv, where the goal is to first build a number of cities (*Initial_M*), grow the population at those cities (*Growth_M*), achieve appropriate technology for military production (*Research_M*), exploit that technology to build a strong military (*Production_M*), and then employ that military to destroy the opponents (*MarineRush*).

In order to produce the adaptations depicted within the bold-outlined boxes of Figure 3, REMng must decide how the game-playing agent should be adapted in order to take advantage of the altered game dynamics of the luxury adaptation scenario. First, REMng must localize the adaptations within the TMKL model, as per the first reasoning step in Figure 2. In order to localize the adaptations, REMng must look into its knowledge base to determine all secondary impacts of increasing the happiness value of a city. Once it obtains this information, REMng must inspect the model of the agent to determine whether there are any goals expressed within the model that could potentially be affected by exploiting the new rule. In this example, REMng's knowledge base contains the information that increasing the happiness value at a city will also increase the population growth rate at that city. By forward chaining from the new rule added in the luxury adaptation scenario, REMng determines that connecting a city to a luxury resource via a road will have a secondary impact of increasing the population growth rate at that city. REMng's subsequent search of the TMKL model will then identify the Growth task (the task parent of the *Growth_M* method depicted in Figure 3) as having a relevant goal, since the goal of this task is to increase population at cities.

Given that one or more such locations are identified, REMng will look into its library of adaptation patterns to determine whether it knows of any ways to adapt the identified model location(s) to achieve some enhancement relevant to the newly added rule. REMng has now reached the second reasoning step in Figure 2, pattern retrieval. If REMng locates some potentially applicable adaptation patterns, it will then try to instantiate them for the current situation (the following step in Figure 2). Adaptation patterns are general, and thus require parameterization to make them game-, system- and scenario-specific. In this scenario, REMng does find an applicable pattern, *insert-action-for-goal*, which inserts processing in the agent's model that results in the execution of an action to help achieve a particular goal. This pattern is instantiated by locating a specific action to be executed (found in the game-specific knowledge base), *ConnectByRoad*. This action causes a worker unit to build a road connecting two locations on the FreeCiv game map. REMng must further constrain the parameters of the action to be executed based upon the specific adaptation scenario. Here, REMng sees that the rule specifically requires the connection of a city location to a luxury resource location, and thus constrains the two location parameters of the *ConnectByRoad* action to those that contain the appropriate items.

Now that REMng has an instantiated the pattern to form an adaptation plan, it can actually apply changes to the TMKL model. The application of this plan includes several more plan-specific reasoning steps, including (1) an analysis of the control flow within the portion of the model to be modified, (2) insuring that there are no resource conflicts between existing actions and those to be inserted, (3) adding secondary actions that establish preconditions of the action to be inserted and (4) the generation of heuristics to control the execution of the action as well as secondary actions arising from (3).

Step (1) finds that the state machine flow in the *Growth_M* method of Figure 3 is sequential and unconditional, and step (2) finds no resource conflicts. Based on these findings, REMng adds a new task to the end of the existing state machine in *Growth_M*. The expanded structure of this new task is based upon REMngs analysis of the action to be executed (*ConnectByRoad*), its parameters, and the constraints on those parameters. Step (3) finds that we may not have the worker units necessary to execute *ConnectByRoad*, so it inserts the new task under the *GrowthImprovements_M* method after a recursive invocation of the add-task-for-goal adaptation pattern set up with a new parameterization for this secondary adaptation. Step (4) is handled by making use of a cost annotation that is attached to the *ConnectByRoad* action within the domain-specific knowledge base. At this time REMng will prefer to execute the lowest-cost parameterizations of *ConnectByRoad*. This is not necessarily the best heuristic, and step (4) is likely a place where the human designer may wish to intervene in order to insert a better criteria for ranking of possible action parameterizations.

REMng then proceeds to the Evaluation step of Figure 2 and displays the model to the user for validation. If the user rejects the adaptation, REMng retracts it and, in this case, terminates, as there are no further retrieved adaptation patterns to be tried. If the user accepts REMng's adapta-

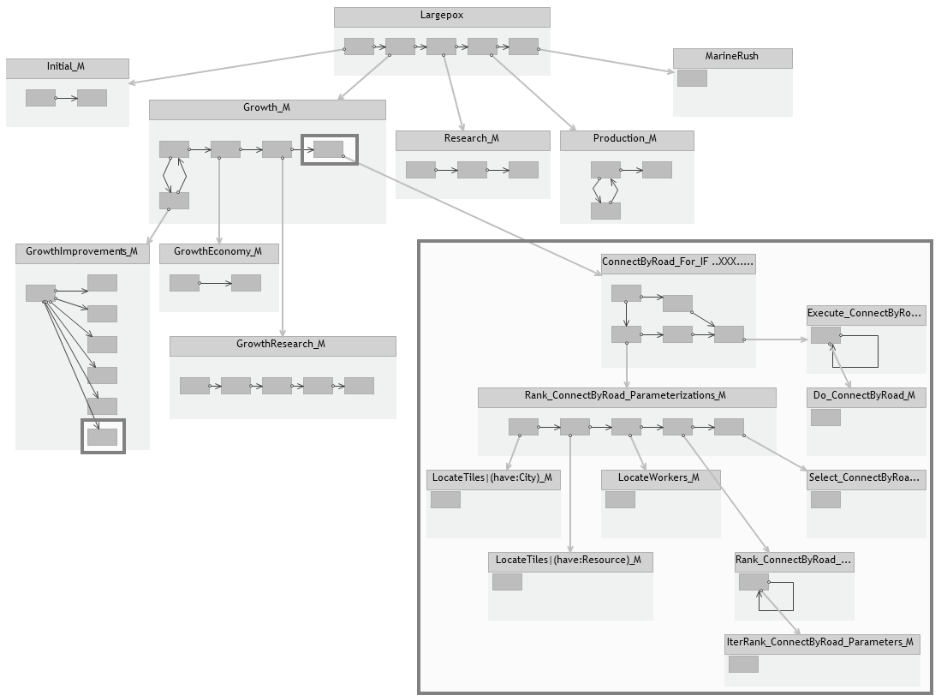


Figure 3: Detailed TMKL model for agent player in the FreeCiv case study. In this figure, the containing, named rectangles are TMKL Methods. The contained, unlabeled rectangles are Tasks. The lines between Tasks in the Methods depict control flow (state transitions) while the lines from Tasks to Methods illustrate which Methods implement particular Tasks. Areas enclosed in bold boxes are added during adaptation in this case study.

tion, the result is a new, adapted TMKL model to be run in the modified FreeCiv environment containing the new game rule. This model is handed off to code generation mechanism to produce executable code for the adapted FreeCiv agent.

Code generation

FreeCiv and its unadapted AI player are written in the C programming language. Adapting the C code directly requires knowledge of both C's syntax and also of low-level implementation details. For the experiment described in this paper, we were more concerned with adaptation at the strategic level. We therefore decided to separate the programming-language-specific issues of reverse engineering and code embedding from the core research question of reasoning about adaptation. To effect this separation, we devised a domain-specific language for modeling games. The language contains both an ontology of game concepts and a reference architecture for game-playing agents. We then manually reverse engineered the FreeCiv AI agent into this language for use by REMng. After REMng produces an adapted model, the code generator produced an updated C program capable of playing the game with the luxury rule described above.

The input to the code generation process is the adapted TMKL model produced by REMng. The result of generating code from the model is a set of C files. These are then compiled and linked with the run-time library to produce an executable program capable of autonomously playing FreeCiv. Generated code comprises a file containing implementations of the finite state machines inherent in the TMKL Methods and a file containing a set of queries of (accesses into) the TMKL knowledge base. The run-time library also comprises the two components responsible for realizing the domain-specific language. The first is a generic robot player capable only of communicating with the game engine on a turn-by-turn basis, sending it any outstanding requests. The means of communication is FreeCiv's game engine API comprising a set of *handles*. The second component contains implementations for *commands*. Commands denote TMKL primitive Tasks for performing actions in the game. When executed, the state machines produce a sequence of commands that are queued for execution by the generic player. When the game engine has completed one turn in the game, the state machines can resume their activities, possibly making use of the compiled queries to learn about changes in the game state. Execution progresses in this fashion, alternating between agent action and game engine updates until the game is completed.

Discussion

We have learned many things while conducting our research with TMKL and FreeCiv. Specifically, we can now begin the process of designing a next-generation teleological language. Interesting extensions include program structures, enhanced inferencing and knowledge modeling, the ability to express non-functional requirements and automated reverse engineering used to produce the original, unadapted TMKL models.

Program structures TMKL is strictly hierarchical and sequential. Unfortunately, real programs are more complex. In FreeCiv it is often the case that conflicting goals must be reconciled. It makes sense to be able to reason about the goals separately and modularly and then use a reconciliation mechanism to arbitrate. For example, having more soldiers supports safety and ultimate victory, but taxes are required to support them, thereby reducing the happiness and productivity of citizens. Furthermore, to model agents capable of concurrent processing or to model independent, concurrently executing agents, it makes sense to add supporting program structuring mechanisms.

Enhanced reasoning REMng is specialized for situations that arise when adapting FreeCiv. The following generalizations are contemplated.

- The ability to handle hypothetical situations.
- The ability to plug in external reasoners such as planners and learners.
- The ability to provide explanations for decisions.
- The ability to support classification and generalization such as would be provided by an off-the-shelf knowledge representation and reasoning system like PowerLoom (http://www.isi.edu/isd/LOOM/PowerLoom/).
- The ability to reason effectively at the meta-level in situations when making strategic decisions involving multiple conflicting goals is required. One possibility is to devise a TMKL model of REMng so that it can reason about itself.

Knowledge modeling The level of abstraction provided by the Knowledge component of TMKL is low. In particular, our experiments with FreeCiv suggest the addition of the following devices to the language.

- The ability to aggregate similar domain elements.
- The ability to aggregate domain operations by, for example, providing by a macro capability.
- A specialized notation for expressing the adaptation to be made. With the FreeCiv experiment, the adaptation amounted to a rule change, but *rule* is a domain concept, and TMKL needs a more general mechanism.

Conclusion

We have described a language, TMKL, and a tool, GAIA, that supports the adaptation of game-playing agents. We have experimented with our approach to agent adaptation in the context of an open-source game called FreeCiv. We have adapted its AI game-playing agent in the situation where a new game rule has been added. A key enabler for this approach is the close connection between the game requirements, as expressed by TMKL Tasks, and the mechanisms by which the requirements are implemented, TMKL Methods. The connections between these requirements and the mechanisms that achieve them are represented by the use of a teleological modeling language, TMKL. These teleological agent models allow a metareasoning process to localize required changes to the modeled agent's design, and then to effect adaptation of the agent at identified locations. The initial work on the adaptation scenario described here lends support to our overarching hypothesis that teleology is a central organizing principle of knowledge representations that enable self-adaptation of reasoning processes. In addition to the enhancements described in Section 5, we plan to experiment first with other strategy games and then move to other types of games, such as first-person shooters.

Acknowledgements

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