Towards Situation Awareness and Attention Guidance in a Multiplayer Environment using Augmented Reality and Carcassonne

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ABSTRACT
Augmented reality (AR) games are a rich environment for researching and testing computational systems that provide subtle user guidance and training. In particular, computer systems that aim to augment a user’s situation awareness benefit from the range of sensors and computing power available in AR headsets. The main focus of this work-in-progress paper is the introduction of the concept of the individualized Situation Awareness-based Attention Guidance (SAAG) system used to increase humans’ situating awareness and the augmented reality version of the board game Carcassonne for validation and evaluation of SAAG. Furthermore, we present our initial work in developing the SAAG pipeline, the generation of game state encodings, the development and training of a game AI, and the design of situation modeling and eye-tracking processes.

CCS CONCEPTS
• Computing methodologies → Neural networks; • Human-centered computing → Ubiquitous and mobile computing systems and tools; • Applied computing → Computer games.

KEYWORDS
augmented reality, situation awareness, knowledge representation, Carcassonne

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1 INTRODUCTION
Augmented Reality (AR) enhances the real world with the addition of computer generated virtual elements. Many senses, smell, touch, hearing, and sight, can potentially be augmented, though the most common application of AR is sight, using a head-mounted display [2]. Several users may simultaneously access and operate a shared digitally augmented environment, either at the same place or remotely. Users commonly interact with each other and the augmented elements in this virtual framework by using hand gestures, movement, and even gaze. The interactive nature of AR, as well as its direct connection to the real world, have produced extensive research work and industrial applications of AR to different fields such as education, entertainment, medicine, and retail [7].

Human-Computer interaction in games (HCI-games) is a very broad field that covers research on the many ways in which human players interact with digital games that, given their interactive, playful, and challenging nature, present a rich field of study separated from human-computer interaction in other forms of software [1]. This also makes digital games a very suitable environment for other areas of research, such as artificial intelligence, user-centered design, situation awareness, pervasive interfaces, collaborative and competitive behavior, and long-term planning [6, 15].

This paper proposes an AR version of the acclaimed tabletop game Carcassonne as a framework for developing a SAAG system
for multi-user digital environments. Here we present the game which we refer to as cARcassonne, the framework for a situation awareness and attention guidance (SAAG) system that we have built using cARcassonne as a testbed, and the initial design of a number of the SAAG modules.

2 RELATED WORK

2.1 Augmented Reality and Games

The rise and evolution of AR technologies is closely related to the advancements in the hardware used for its implementation; this includes displays such as headsets combined with a variety of sensors and controllers that enable the user to interact in a mixed reality environment either virtual or physical objects. The applications of AR have been many in areas such as retail, healthcare, immersive prototyping, education, aeronautical, and military [11].

One of the most prolific sectors in the application of AR and mixed-reality has been games. As in other areas, games are a very fitting platform for prototyping and benchmarking approaches that make use of relatively unexplored technologies or novel algorithms [14]. The immersive and world-integrated nature of AR games provides a unique opportunity for studying computer augmentation and guidance of real-world tasks. In addition to creating the ability to add audiovisual cues to a user’s environment, AR headsets include sensor systems that can track a user’s response to stimulus, including motion sensing and gaze tracking. These digital sensors can feedback into the process of learning from user behaviour to further improve the augmentation systems.

2.2 Situation Awareness

Among the fields that can be advanced by AR is situation awareness. Situation awareness, originally defined as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” [3], is often applied to complex situations. Situation awareness is critical for decision-making and action-taking [4], which in turn means that improving individual human’s situation awareness will improve the decisions and actions of individuals.

However, AR games provide a low-risk environment in which a user’s situational awareness can be assessed and computational tools to improve their awareness can be prototyped and tested. Ensley’s original situation awareness model proposes three phases of situational awareness: perception of the situation, comprehension of the perceived data, and projection of the situation into the future [3]. AR systems have a wealth of tools that can be used to perceive the situation in analog and digital spaces. They also have the computing power to process those inputs into models of the situation that can also be used to project future situations.

3 SYSTEM OVERVIEW

The ultimate goal of this research is the development of a computational system to augment a user’s situational awareness during Carcassonne gameplay. The intent is to assist a novice player in appreciating the full extent of a scenario by recognizing players’ intentions and gently guiding them towards more advanced strategies.

In this context, we have designed the proposed SAAG system (fig. 1). The proposed system updates the original model of human situation awareness [4] to differentiate between computational processes and human processing of the situation. The work presented in this paper focuses on three modules of the situational awareness component (SAc) of SAAG: Perception, Situation recognition, and Intention recognition.

The Perception module is used to perceive the real environmental objects and combine this information with virtual object’s information to create a mixed-reality situation representation denoted situation model (section 3.2). In the next module, Situation recognition, the situation model is used to assign the given situation to a situation class. Hereupon, the situation project is performed specifying the possible upcoming situations considering the given situation. Using perceived information from the perception module about the given situation and the user-related sensory data like eye-tracking, Intention recognition is realized (section 3.4). Based on the Situation projection providing the information about most likely upcoming situation options and the user’s action estimation provided by the Intention recognition module, the decision regarding optimal user stimuli is determined by the Decision-making module. The mentioned modules are detailed in the following sub-chapters. However, for a better understanding of the testbed the Carcassonne game and our AR-focused implementation denoted cARcassonne are introduced first.

Perception refers to how the computer is able to gather information about the system state. As the gameplay is digital, there is no sensory perception performed by the system per se, but the encoding of game data is part of the perception process. A pair of encodings of the Carcassonne game state, detailed in section 3.2 are one of the major contributions of this work and represent the perception block in the SAAG process. Situation recognition occurs in the form of the situation model described in section 3.4. Situation is defined, in this work, as the likelihood of each of the legal placements of the next tile in play in a given game state and the situation model attempts to capture the typical decisions that a player might make in a particular scenario. Intention recognition utilizes the data representing a user’s gaze along with the situation
model to attempt to discern their likely placement. This module is in its infancy and its initial development is discussed in section 3.5, while planned future work is detailed in section 4.

One challenge that arose in the development of these systems was the lack of available datasets detailing the progression of Carcassonne games. Our solution was to develop an AI to play Carcassonne, both to generate large databases of AI-versus-AI games that could be used in training the situation model, and to provide an AI opponent for human players. This AI is detailed in section 3.3.

3.1 Carcassonne and cARcassonne

Carcassonne [13] is a tile-based strategic board game for two to five players, originally published in 2000, and awarded with the Spiel des Jahres prize in 2001. This preceded an enormous popularity in the coming years that has made it, and its countless expansions and updates, one of the best-selling tabletop games in history.

It is named after the medieval fortified town of Carcassonne in southern France. This setting is used to challenge players to build, tile by tile, a common landscape where features such as cities, roads, and fields can be created, owned by players, and then scored to win the game. In their turn, players draw a random tile from a common stack, that they then have to place adjacent to any other already placed tile on the board, in a way that their composing features adequately aligned (i.e. roads and cities don’t end abruptly and build onto each other). Finally, players may place a so called meeple on one of the features in the placed tile to be able to obtain points from it, provided that it is not previously owned by other player. However, it is possible for some features to be shared by opposing players, either intentionally or not, opening scope for punctual player-player interaction in both, competitive and cooperative fashions.

The AR version of Carcassonne, cARcassonne, that we have been developing for this research implements the most basic rule set of the original board game. It is designed to be played using the Hololens 2 AR headset, which projects a virtual table into the player’s physical environment (fig. 2). Players draw tiles and meeples using a virtual button and then are able to pick up, rotate, and place the game pieces with actions that are similar to playing a physical version of the board game. Audiovisual cues indicate to the player whether their placement is legal and their turn is ended by ringing a virtual bell that sits at the side of the table.

3.2 Perception and game state encoding

The Perception module generates the situation model based on the information about the physical and virtual environment. For the presented example, in this paper, we have decided, for simplification purposes, not to distinguish, between the generation of the situation model as part of the Situation perception module and the game state encoding. The representation of a game that is used in computational processing informs the way that the computational systems are able to learn models and representations of the game situation. It is important that the game state encoding is able to capture all important features of the game in a compact and efficient representation that creates in the given case the situation model.

We developed two complimentary game encodings for the Carcassonne board that are used in different contexts. A Bit encoding is used in visualizations of the game board as well as in the convolutional neural network (CNN)-based learning processes that train the game AI (section 3.3). A Graph encoding is used in the game engine to determine legal moves and scoring of game features, but also forms the basis of the graph neural network model for the situation projection (see section 3.4).

For the Bit encoding, each tile is divided into a 3x3 sub-tile grid. Each grid cell is represented by a bit field that holds a representation of the features in that part of the tile including for cloisters, roads, cities, and fields. The entire game board is represented as a 120×120 sub-tile matrix where spaces without placed tiles are

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1We found experimentally that games do not extend more than 16 tiles in any direction from the initial tile, so that a 40×40 game board is sufficient to capture the extent of normal gameplay. Each tile has a 3×3 sub-tile representation, so a 120×120 matrix can represent the whole board as sub-tiles.
Each Carcassonne tile consists of four potential connections, the physical, spatial layout of the vertices on a tile. Feature connections (yellow) represent the logical connections between vertices. Vertices on a single road or that form a single city are all connected by a feature connection. Inter-tile connections (blue) are formed when two vertices are placed adjacent to one another on the game board.

The graph representation is used extensively in the game’s underlying logic system. Graph methods enable rapid and robust computation of feature completion, the legality of a game piece placement, and scoring. Furthermore, since this representation is used as the situation model, it forms the basis for the graph neural network-based situation recognition and projection (section 3.4).

### 3.3 Game AI

The game AI is a CNN-based agent that plays Carcassonne, selecting the placement of a tile and an optional meeple based on the current state of the game. Unity’s built-in ML-Agents framework [8] is used to train the agents and to play games once training is complete. The game AI is used as a SAAG system supporting function both to generate game situations for training the networks for situation recognition and projection (section 3.4) and as an opponent for human players.

To engage with the game, the agent receives an encoded representation of the game state, referred to in ML-Agents as observations. Observations are collected as a 120x120x5 tensor with the first two dimensions representing the width and height of the sub-tile matrix of a 40x40 game board. The final dimension holds five observable variables for each sub-tile: cloister, road, city, shield, and meeple. The cloister, road, and city dimensions are drawn from the Bit encoding of the game state and these are treated as boolean fields where 0 and 1 indicate the absence and presence of a feature, respectively. For the meeple layer, 0 indicates the absence of a meeple, and placed meeples are indicated with a value representing the player to which the meeple belongs. In addition, observations indicating the score, current tile state, and number of tiles and meeples remaining are passed to the AI.

The tensor representation is not the default mode of representing data in ML-Agents — the most basic mode of representation is an observation vector. However, it is essential here to maintain the spatial relationships between game pieces for the neural network.

Given a set of observations, the neural network produces an action within a defined action space. To properly limit the set of actions to the legal positions of tiles and meeples on the board, the action space is defined as a vector representing all possible tile rotations, placements, and meeple placements on the game board. For the 40 × 40 game board used here, this means there are 38400 possible actions. The action space is masked so that, on any given turn, only legal action choices are available.

Our initial approach to training used ML-Agents’ adversarial self-play mode to train the neural network playing against itself. Self-play is a form of reinforcement learning where agents play against past iterations of themselves to learn how to play against opponents of ever-increasing difficulty.

The first attempts at this approach were unsuccessful. Despite training for 1M steps (around 14k games), the agents were not learning even the basic strategies for success in Carcassonne. They would play all of their meeples immediately instead of reserving some for high-scoring opportunities later in the game, and their tile placements were not designed to expand existing features that they owned. We next attempted to train the agent in a single-player game with the goal of gaining as many points as possible to see if the agents learned to complete features and we observed the average number of meeples remaining every turn rise.

Future work on this module will include the addition of curriculum learning to develop agents that first learn gameplay strategies and subsequently focus on an opponent. Additionally, human opponents (section 4) will be used to generate datasets for imitation learning that may be able to help learn Carcassonne strategies more effectively.

### 3.4 Situation recognition and projection

Situation recognition and projection are used to understand the given situation and predict possible upcoming situations. In the
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Figure 4: Metrics from single-player training. The agents can be seen learning the game strategy as they slowly increase the number of cities that they complete over the course of a typical game. They can also be seen holding on to meeples for longer, and getting meeples back as features are completed, leading to a growth in the average number of meeples remaining every turn. Finally, they are gaining points on more turns, indicating that they are adding to features that they already own instead of randomly placing tiles.

The network consists of two graph convolutional network (GCN) [9] layers separated by a ReLu and dropout layer. A pooling layer after the final GCN averages the values of all of the nodes on a single tile. The GNN outputs a floating point number representing the network’s estimate of the probability that a given position and rotation will be selected for the upcoming tile.

3.5 Intention recognition

Using the built-in eye-tracking capabilities of the Hololens 2, we have begun work on the Intention recognition module. Two approaches have been evaluated. The first logs the users’ eye movement over a specified period of time and generates a heatmap indicating where they have spent the most time looking (fig. 6b). The second generates gaze plots that include information not captured by a heatmap like the order and duration of focal points in a user’s gaze path. This temporal aspect of a user’s gaze could be important in predicting their intended actions [5]. The gaze plot can be treated as a graph with the focal point nodes linked to nodes already present in the situation model, meaning this type of data could be readily integrated into the existing GNN-based model.

4 FUTURE WORK

The implementation and initial testing of the various modules of the SAAG system presented in this contribution form the basis for an integrated computational system for augmenting user situational awareness. However, many of the components suffer from a common problem in machine learning — the lack of high-quality datasets for training[16] and will be address as part of future work. In particular, generating realistic human play in the ML-Agents framework has proved challenging. Collecting gameplay data from human players of all levels, however, will provide an improved initial dataset for training the ML-Agents and dedicated networks. It could also serve as a basis for a more effective gameplay AI training process, using imitation learning techniques [12] to develop basic gameplay strategies. We have planned to conduct a dedicated study in collaboration with Lund University’s Humanities Lab. Participants will play a version of the game on a desktop computer in the lab environment against a mixture of human and AI opponents and their games will be recorded for future use in model training.

In addition to gameplay data, the Humanities Lab study will also provide an extended set of eye-tracking data associated with Carcassonne gameplay. The Humanities Lab is equipped with Tobii Pro Spectrum eye trackers [10] which will enable the capture of high-quality eye-tracking data during gameplay. This data will be linked to game state data as well as player move choice information.
Figure 5: Graph representations of the current board (a), next tile (b), and the candidate board (c).

(a) Current board

Figure 6: Mockups of gaze data.

(b) Next tile

(a) AR game board with graph representation overlay.

(b) Heatmap showing player’s gaze, darker colours indicating longer dwell.

(c) Candidate board (candidates marked with *)

(c) Gaze plot overlayed on board and graph, showing gaze order and duration.

It will assist in the study of the relationship between eye movement at various game phases and the player’s strategy and intentions with respect to tile placement.

In this work, a preliminary design of three modules of the SAAG system is presented and evaluated for the developed Carcassonne gameplay. Future research should further improve and evaluate these initial development of the modules and findings by applying the proposed system to other strategic games. In addition, further work is certainly required to develop and evaluate the other proposed components of SAAG including behavior modeling, decision making, and attention guidance.

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