Context-aware Gaze Prediction applied to Game Level Design, Level-of-Detail and Stereo Manipulation

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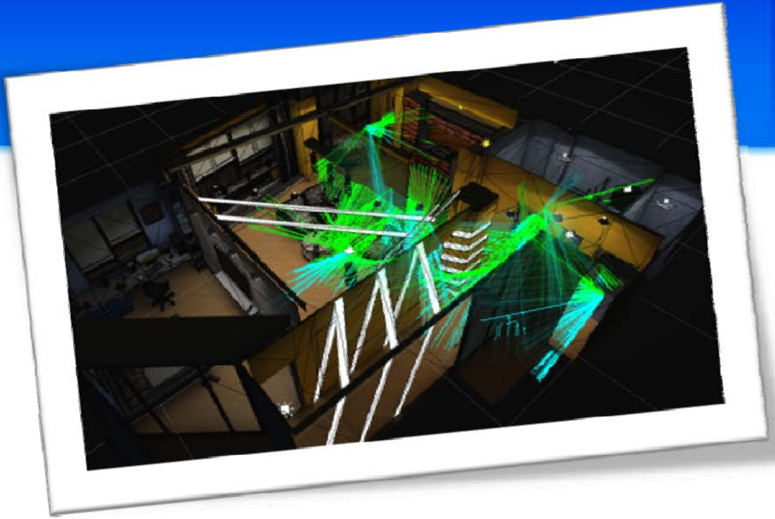
Overview



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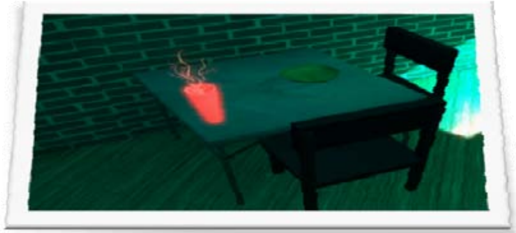
- Problem Statement
- Contributions
- Background
- Part 1: An Automated High-Level Saliency Predictor for Smart Game Balancing
- Part 2: C-LOD: Context-aware Material Level-of-Detail applied to Mobile Graphics
- Part 3: Gaze Prediction using Machine Learning for Dynamic Stereo Manipulation
- Summary



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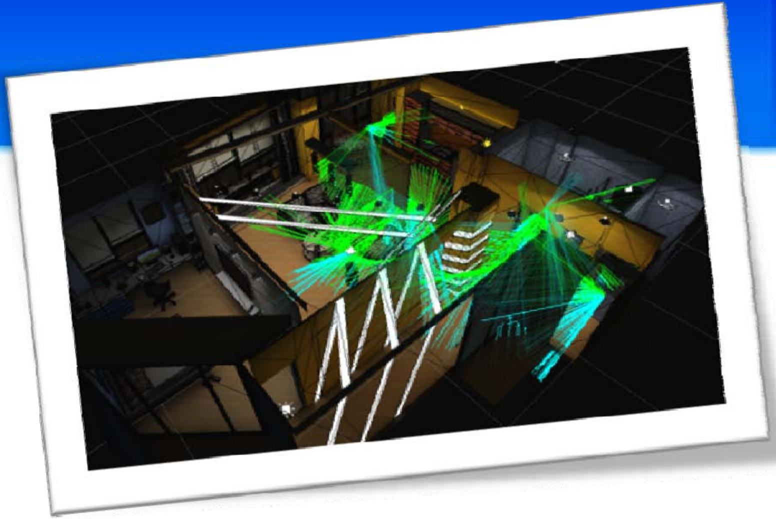

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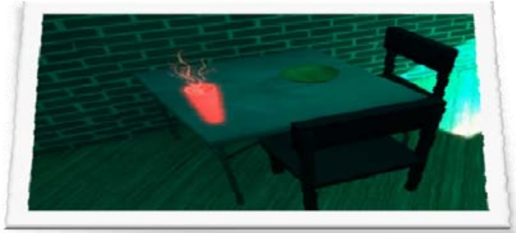
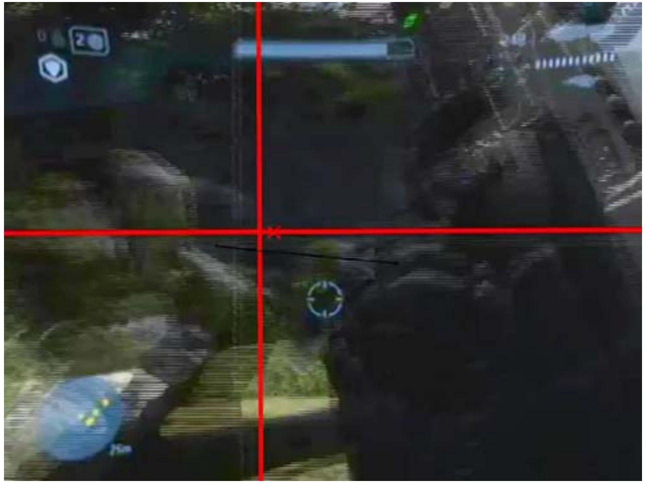


Gaze-aware applications
Motivation

Predicting gaze over a synthetic scene

Knowledge of attended regions in a synthetic scene yields three classes of applications:

- Manipulating observers' gaze to fixate on selected 3D objects based on application goals
- Saving computational resources in regions that will not be attended by reducing rendering quality
- Applying gaze-aware visual effects, e.g. stereo manipulation or tone mapping



VIDEO: ASL Gaze Tracking

Gaze-aware applications
Context

Game Level Design: Manipulating observers' gaze to fixate on selected 3D objects based on application goals

- Many game genres gameplays rely on a target detection task to solve riddles and advance gameplay
  - "Find the object"
- Object placement during level design correlates to search task completion time
  - Implicitly defining game difficulty
- **Currently, designing game levels is a tedious manual operation** (*Pagulayan et al., 2003*)
- **An accurate gaze prediction model allows us to relocate objects estimated to attract visual attention, implicitly adjusting game difficulty**

Gaze-aware applications
Context

Level-of-Detail (LOD): Saving computational resources in regions that will not be attended by reducing rendering quality

- **Higher** rendering quality on areas expected to attract visual attention
- Rendering quality **decreased** for not attended scene areas
- **Current attempts on gaze-aware LOD limited due to limited prediction accuracy** (*Cater et al., 2003*)
- **The accuracy of the gaze prediction model determines if quality reductions are perceived**

LOD on Mobile Devices

- Interest recently renewed due to explosive growth of the mobile market
- Prohibitive hardware restrictions of mobiles for complex effects

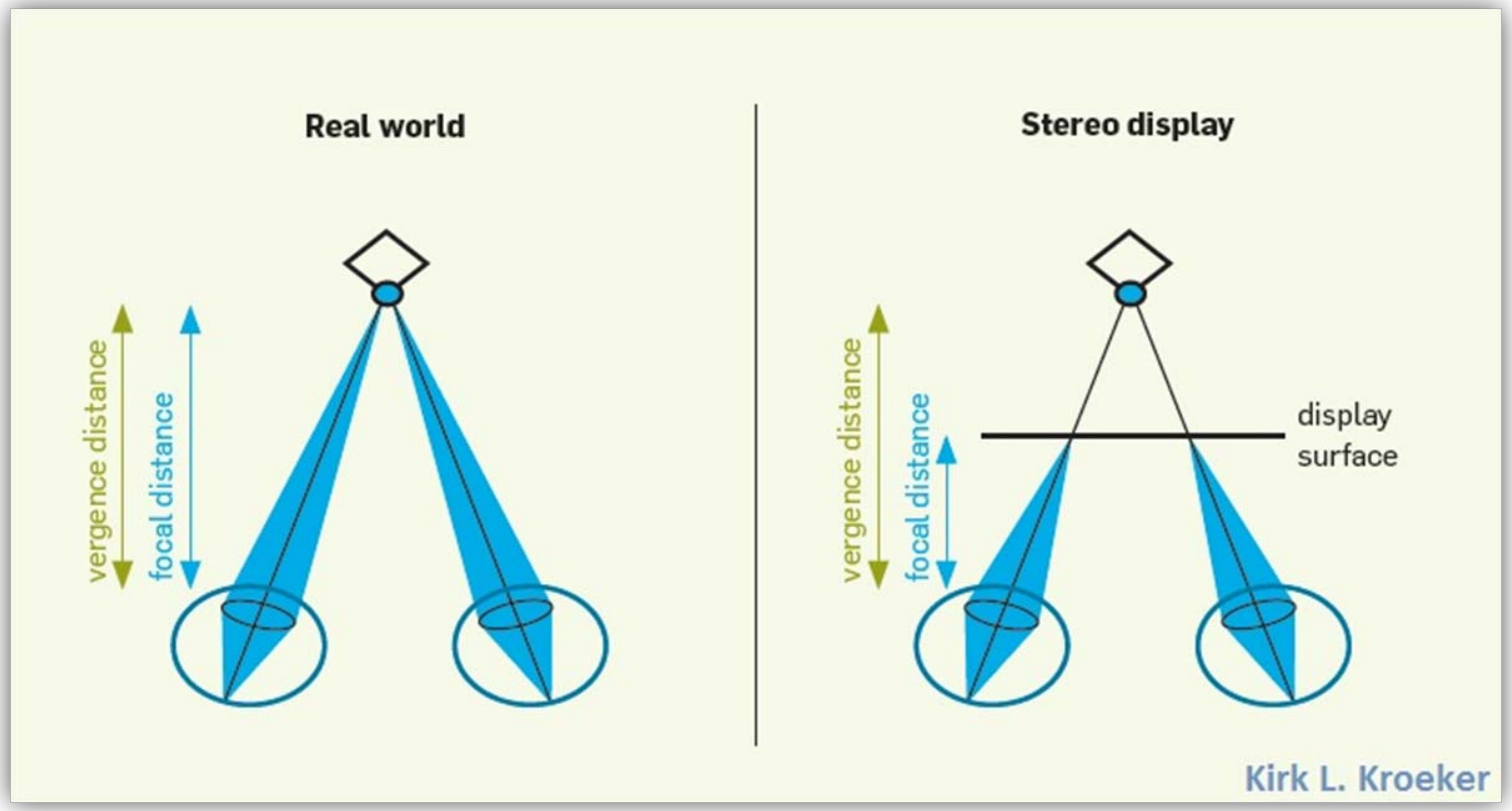
Gaze-aware applications
Context

Comfortable Stereo: Applying gaze-aware visual effects

- Recent popularity of commodity Head Mounted Displays, e.g Oculus Rift
- **Vergence-Accommodation Conflict**

Gaze-aware applications

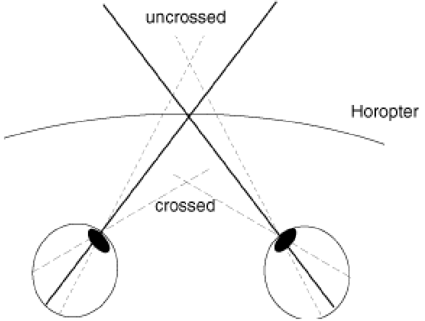
Vergence-Accommodation Conflict



Gaze-aware applications
Context

Comfortable Stereo: Applying gaze-aware visual effects

- **Current *stereo grading* methods based on saliency estimates**
  - Are offline (*Lang et al., 2010*)
  - Apply a global scene depth compression irrespective of attended objects (*Oskam et al., 2011*)
- Need for reduced discomfort and eye-fatigue **without sacrificing depth (cardboarding)**
- **Relocate attended objects in the *disparity comfort zone*!**



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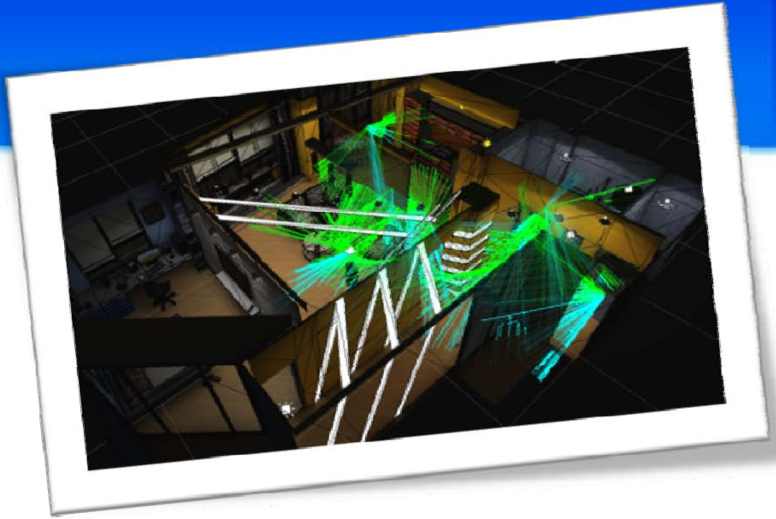

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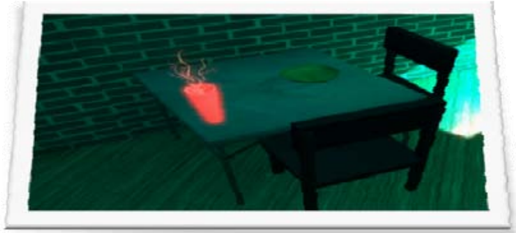
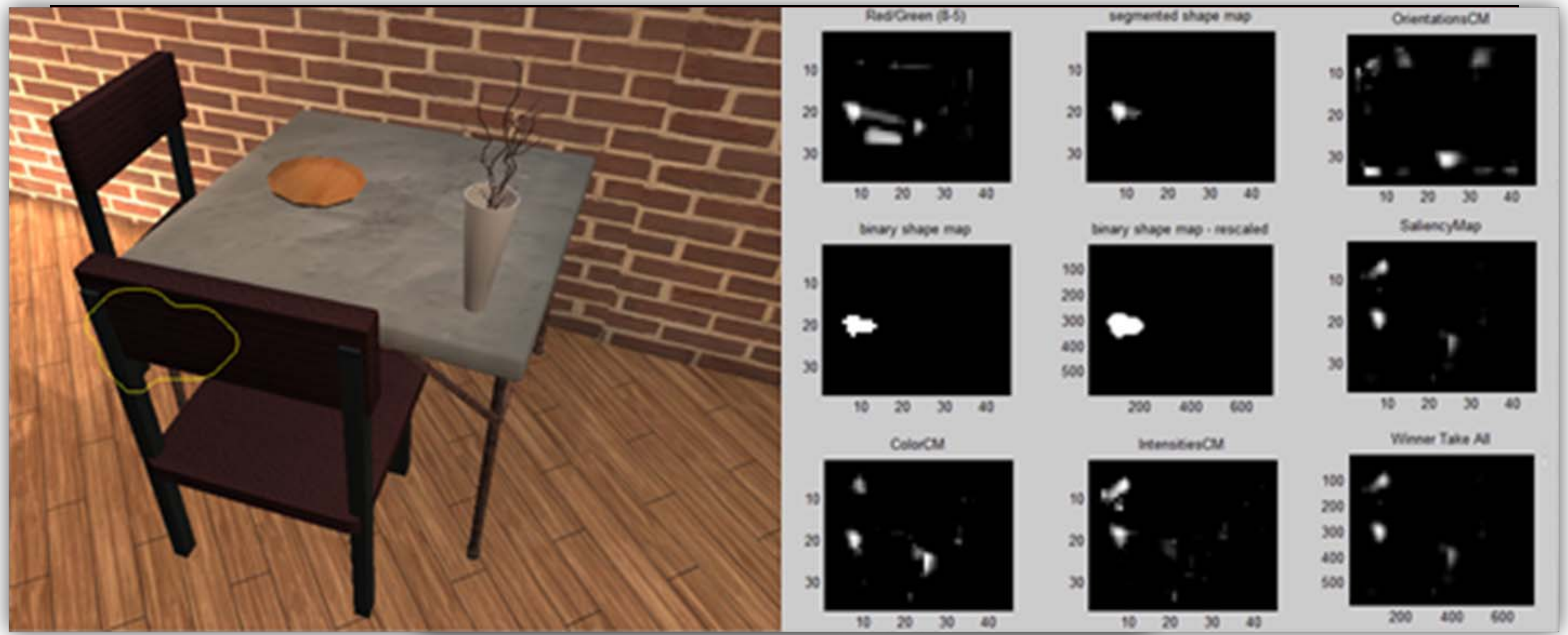


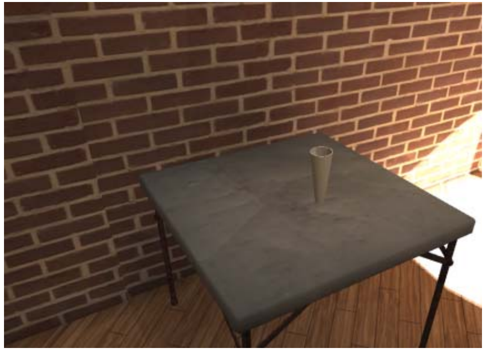
Gaze-aware applications
Problem Statement



Gaze-aware applications
Problem Statement

However, existing low level, image-based gaze prediction models often fail to predict gaze

- High-level properties such as **scene semantics, attention to objects** or **task** affect gaze fixations
- **Object-context semantic relationships are NOT TAKEN into account by existing low level visual attention models**
- It is a **challenging** problem to quantify qualitative object-context relationships



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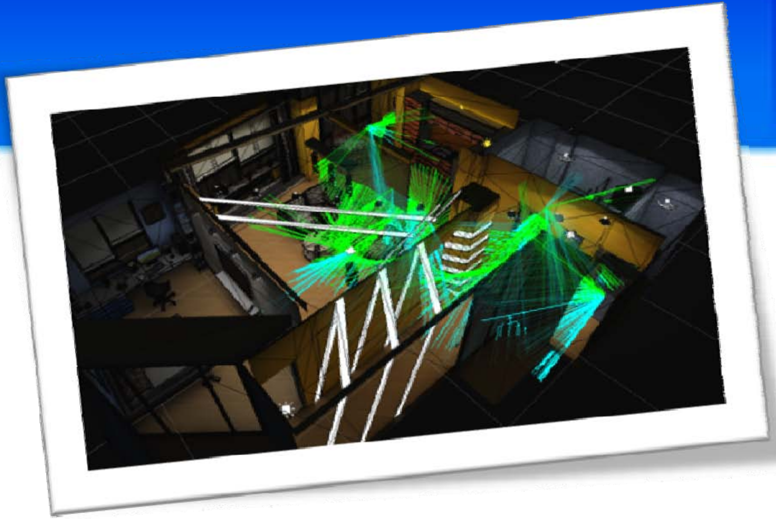

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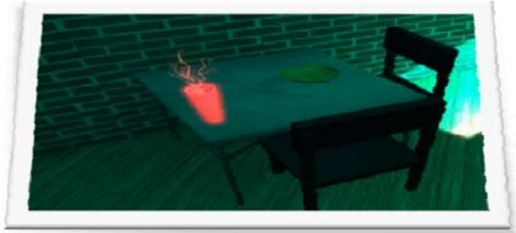


Contributions

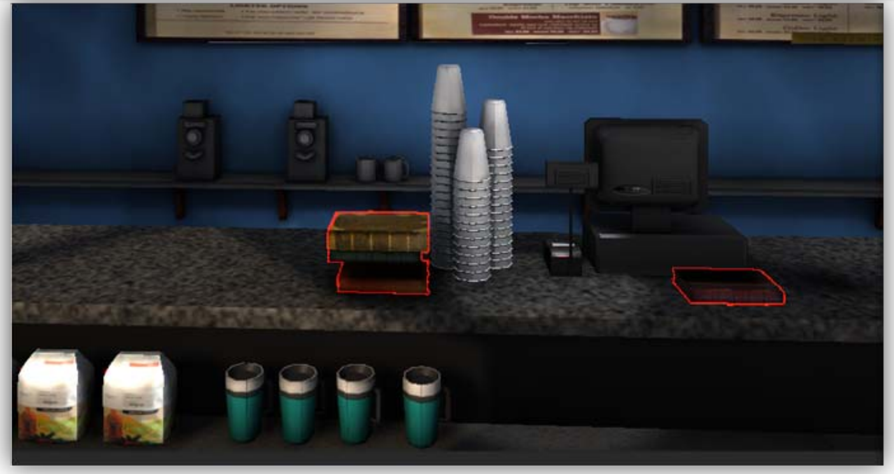
Contribution 1

1. A physically plausible High Level Saliency Model (HLSM)

Encodes six hypotheses from perception and cognitive science into mathematical equations that describe

- Semantic inter-object relationships (e.g. contextual validity, object-context consistency)
- Intra-object positional properties (e.g, object rotation)
- Object topology in terms of inter-object distances and placement (e.g. object isolation)

We developed a computational model that can estimate fixation guidance based on context



Contributions

Contribution 2

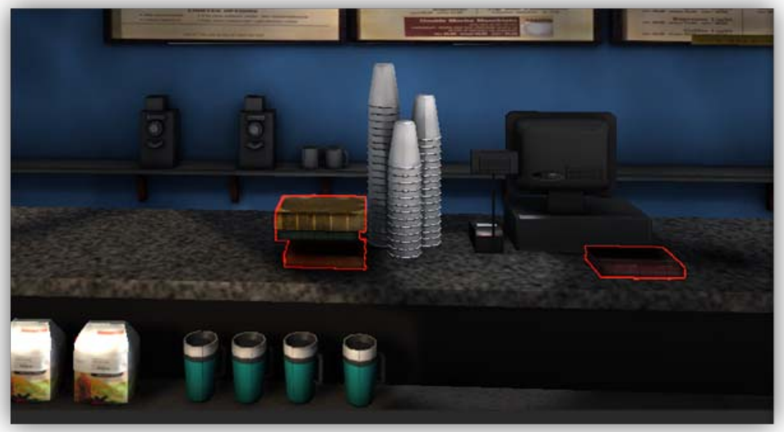
2. A Machine Learning (ML) based predictor

Our Decision Forests-based predictor

- Is automatic avoiding the need for embedding contextual information to objects
- Yields high prediction success rates, **learning** from ground truth eye tracking data
- Supports object motion in contrast to previous task-based and high level approaches

Contributions

Two models of visual attention



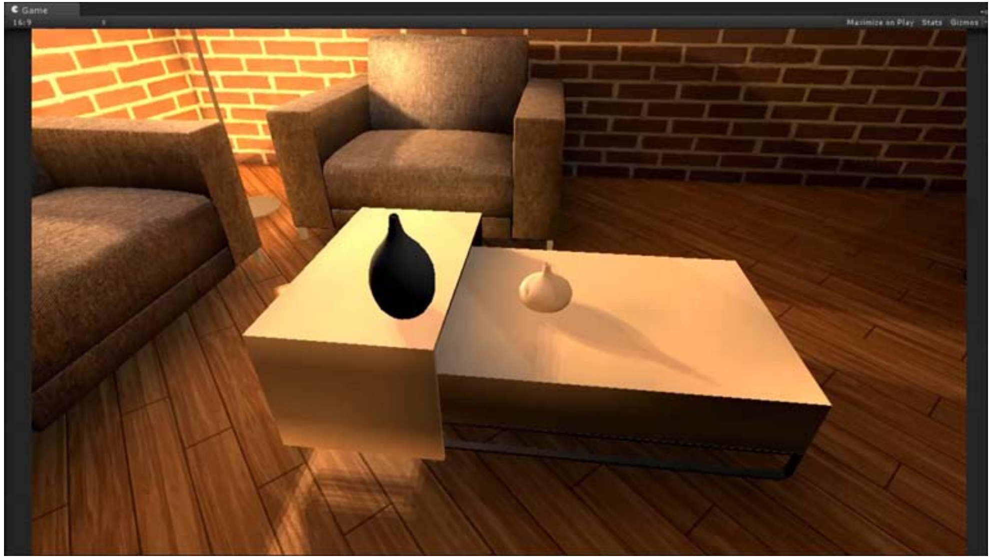
Each model specializes to a different class of applications

- The HLSM does not need eye tracking during model formation; needs semantic object tagging
- The ML-based model does not require object tagging; needs an eye tracker during model formation

Contributions
Contribution 3

3. A game balancing paradigm based on attention

- We develop a system based on the High Level Saliency Model to automatically predict gaze in real-time
- We validate the system's efficacy in adjusting game difficulty by altering object location based on predicted gaze



VIDEO

Contributions

Contribution 4

4. A Level-of-Detail method based on attention for mobile devices

- We present a perceptually optimized renderer for mobile platforms that reduces computation complexity and maintains a more stable frame rate by automatically removing perceptually non-important details
- Enables the usage of - otherwise omitted - complex effects such as subsurface scattering & complex refraction in low-power devices by applying them sparingly only in regions that are expected to be attended

VIDEO

Contributions

Contribution 5

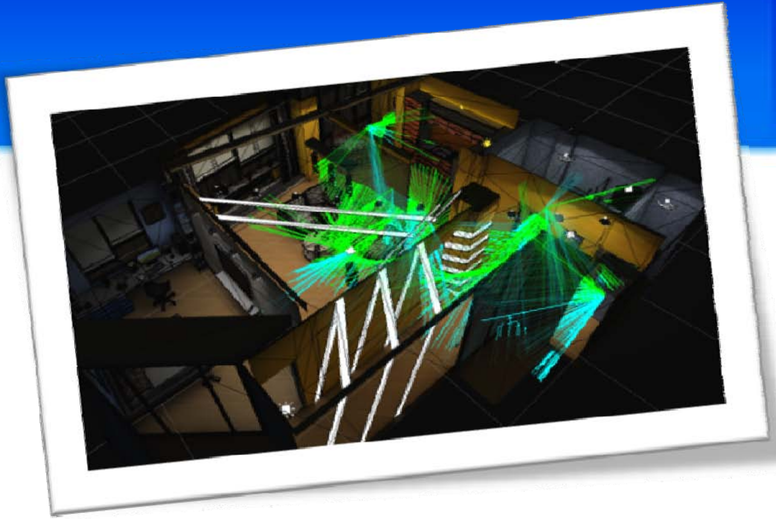
5. A gaze-based stereo manipulation method

Our gaze-aware, localized stereo grading approach

- Provides a greater sense of scene depths than previous global depth compressing methods
- Maintains the same levels of viewing comfort when compared to the state-of-the-art

VIDEO

Overview

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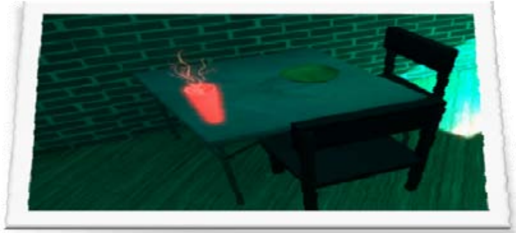
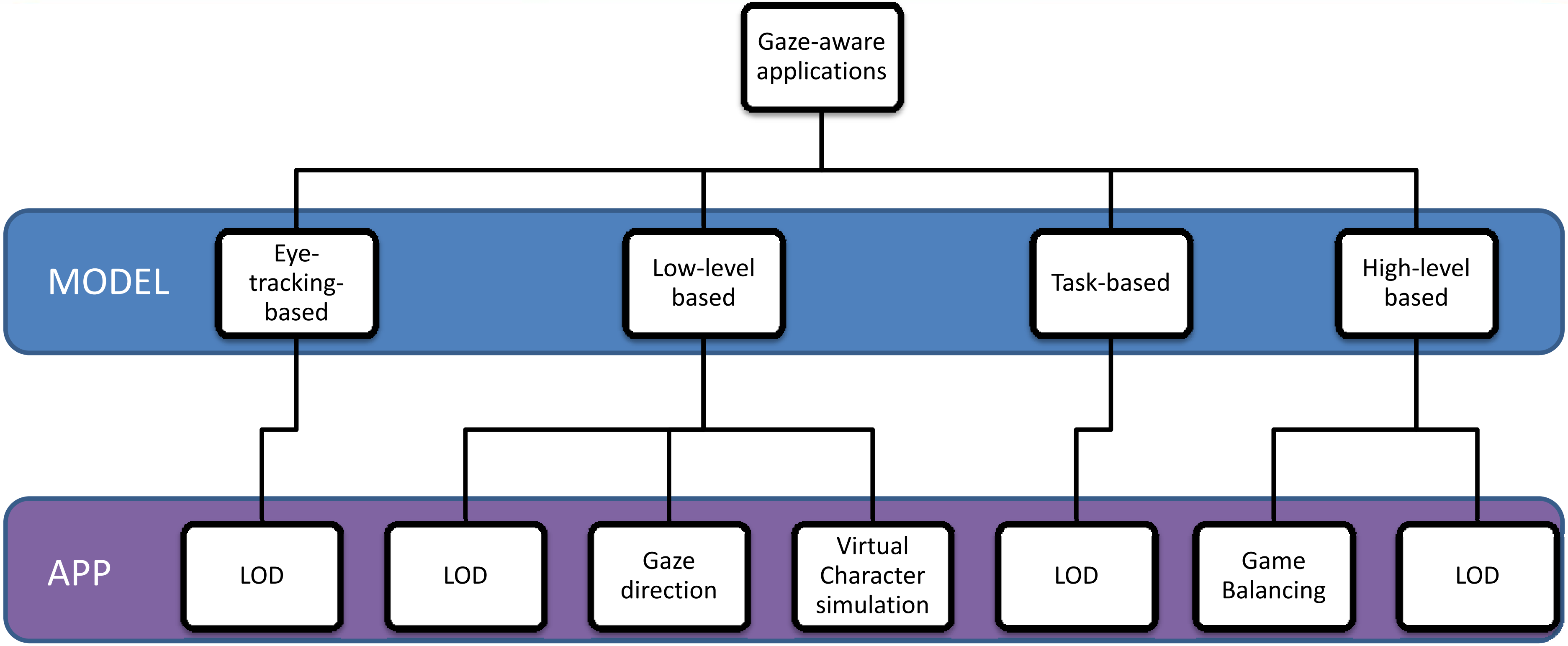


Outline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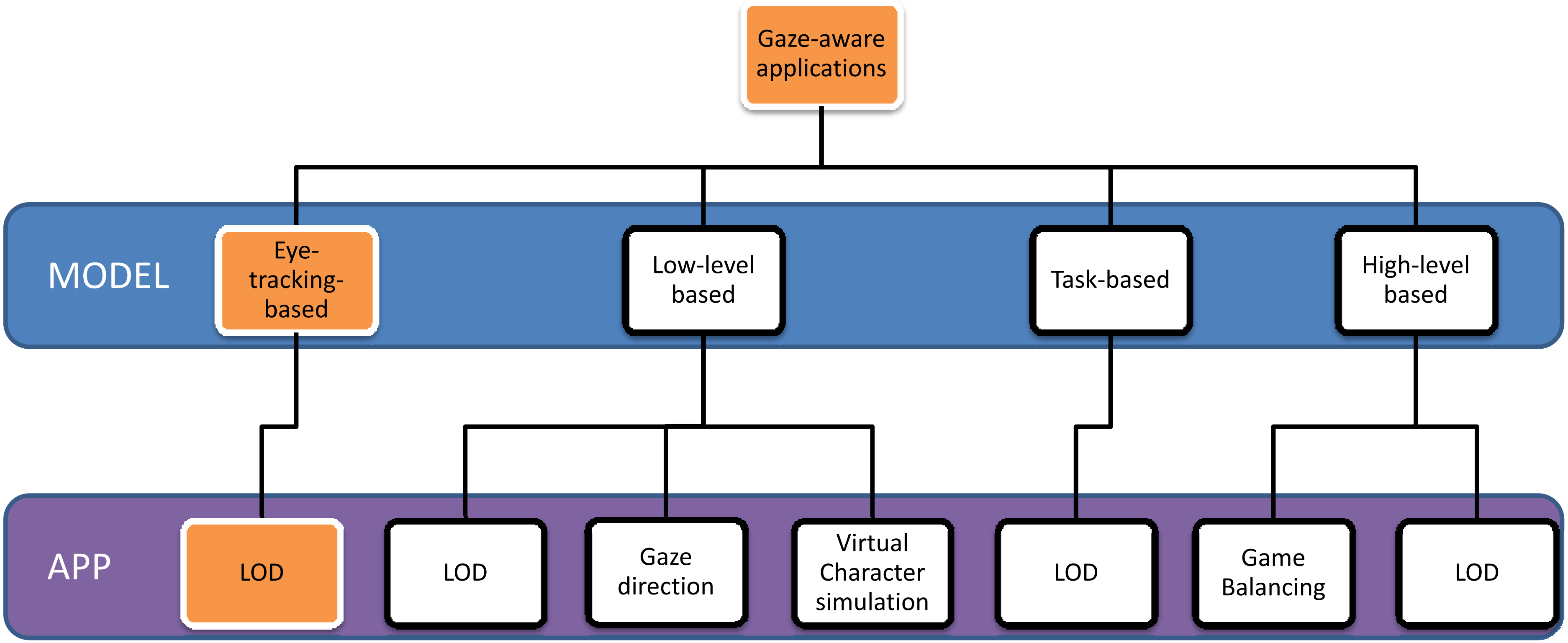
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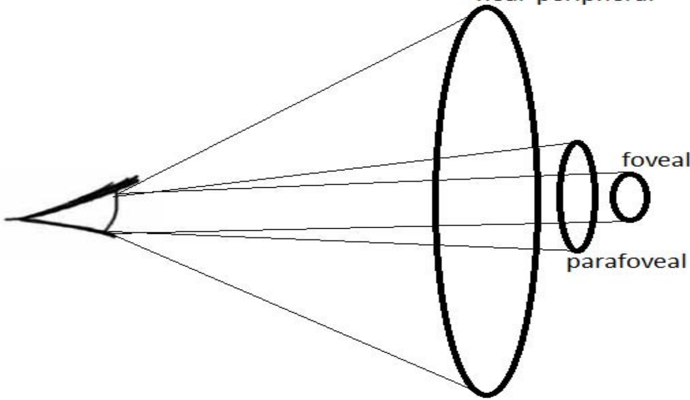
Eye-tracking based gaze prediction

Level-of-Detail

However!

- Latency
- Rarely available for common applications



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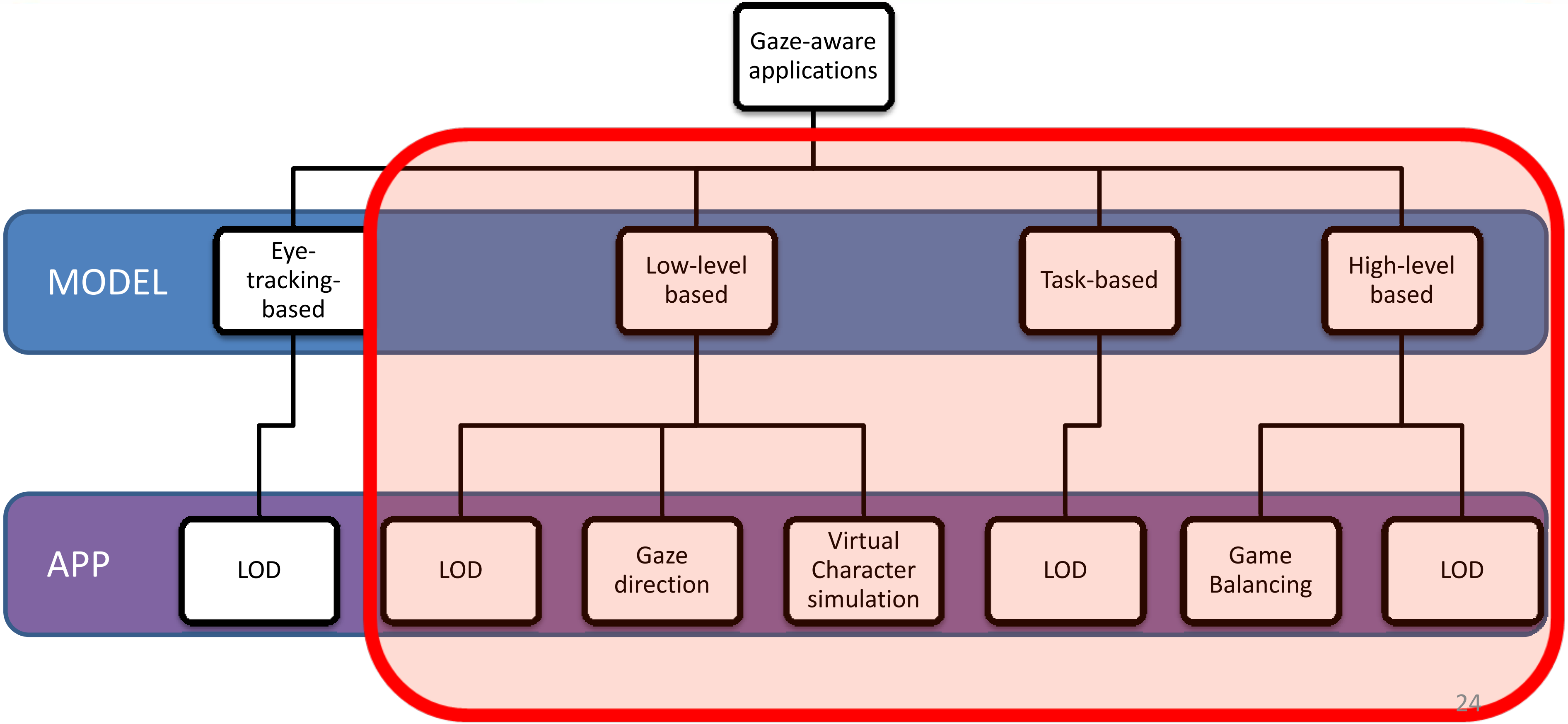
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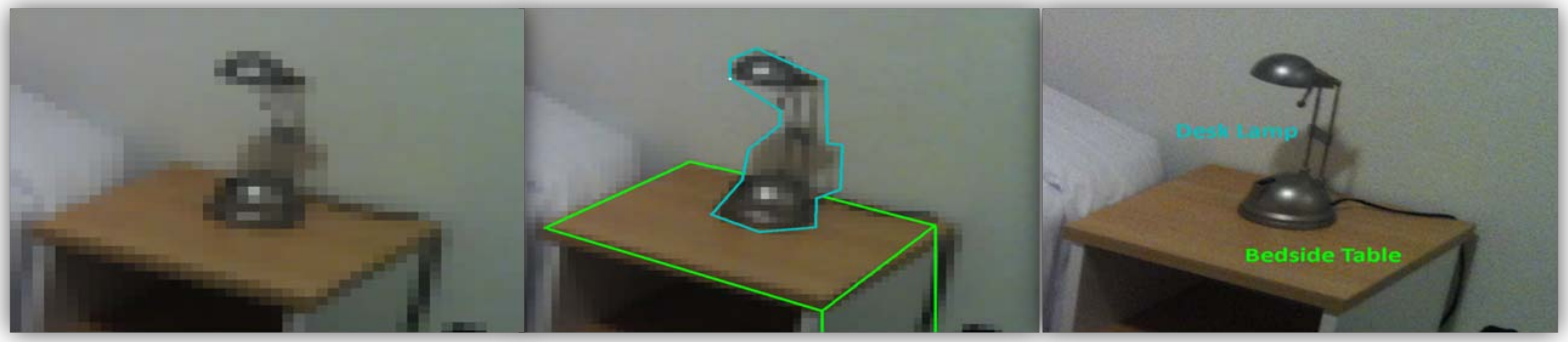
Visual Perception

Levels of abstraction

Active extraction and manipulation of environmental information ***Marr et al., 1982, Shipley et al., 2001***

- Low-level processes extract image regularities e.g. edges, color
- Mid-level processes combine regularities to form features e.g. object shapes
- High-level processes map mid-level features to meaning and semantics



Focal Attention

The selection mechanism of the brain

Mid- and high-level processes have limited resources

- Focal attention selects a few low-level features that are likely to be important
- Low-level features e.g. edges may attract focal attention almost reflex-like

Mid- & high-level features and goal-oriented properties can direct Focal Attention

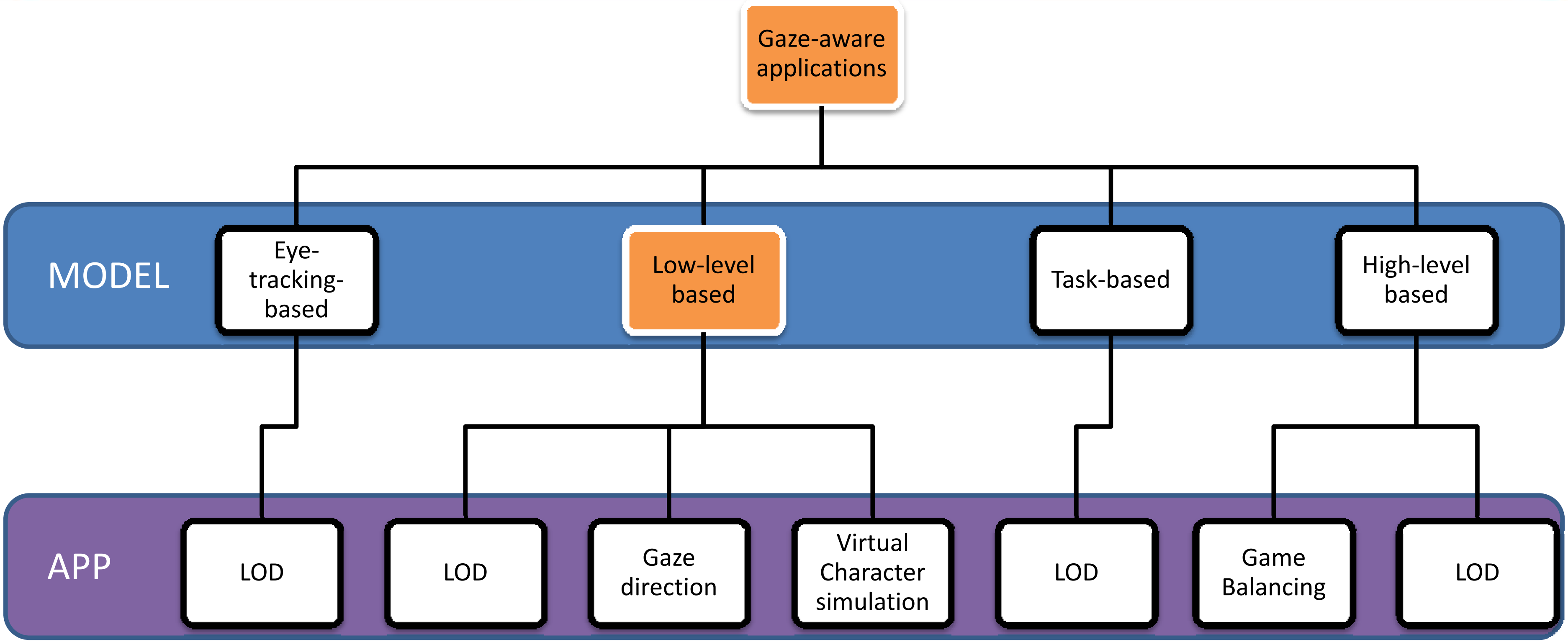
The contextual validity of an object's location affects visual search

✓ When looking for a chimney, usually we direct our gaze first to the rooftops

How are these features combined?

The relative contribution of low-, mid-, and high-level factors on attention is unknown

Outline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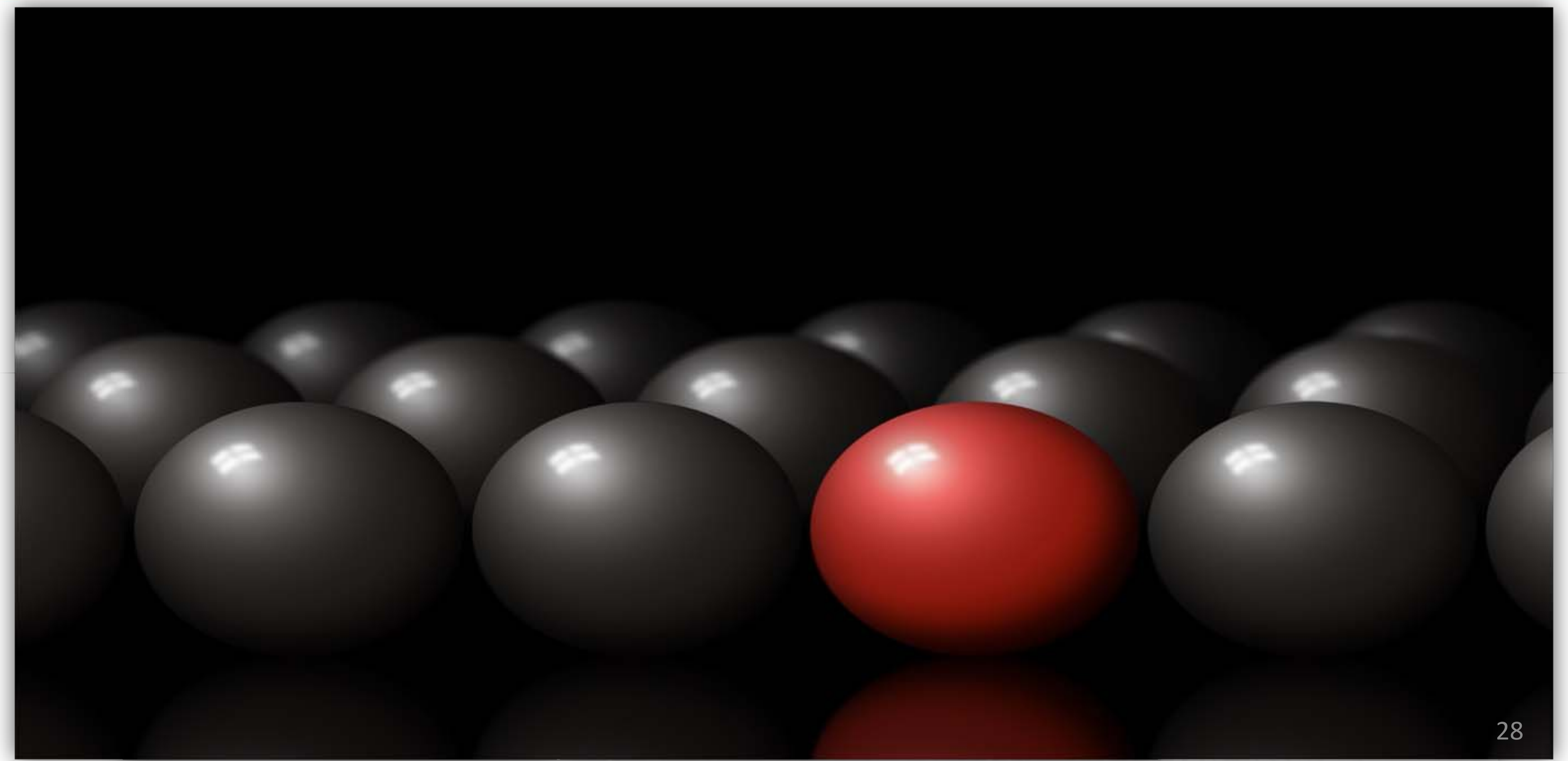
Attention prediction

Saliency based on Low-level image features



Focal Attention Models

Feature Integration Theory (FIT): A two staged-model

Stage 1

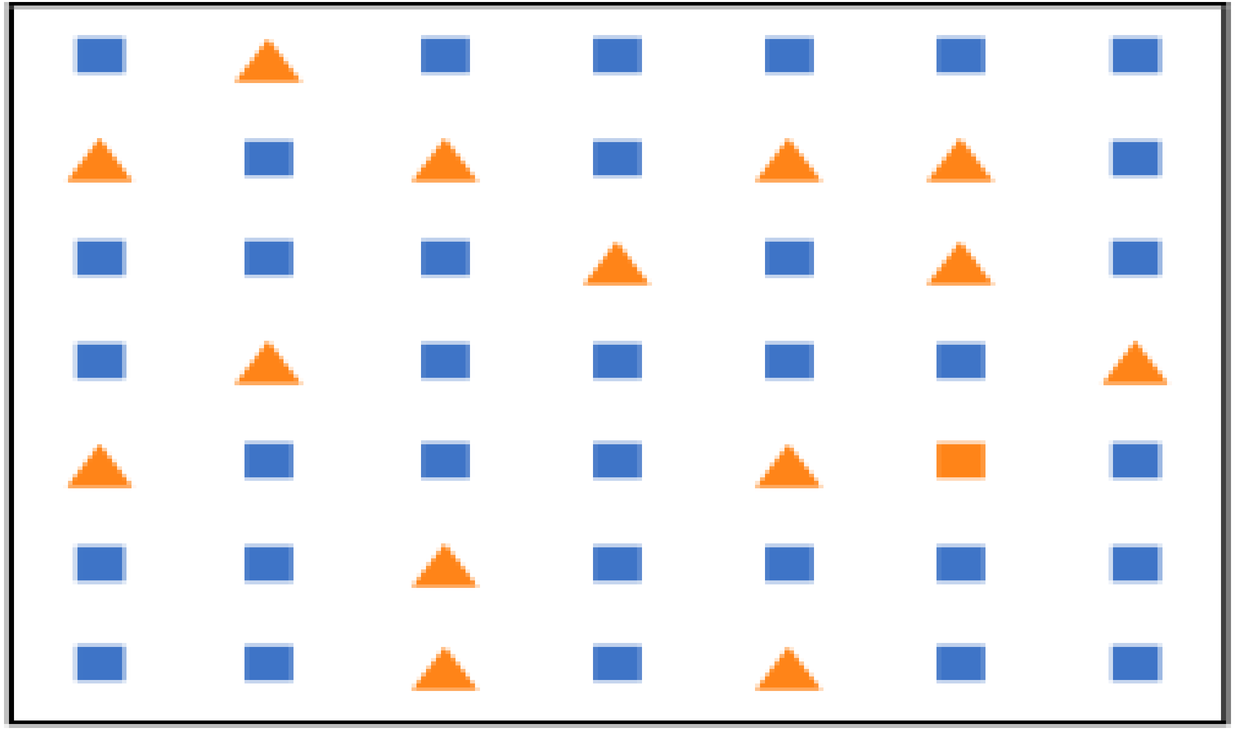
- Low-leve
- Focal att

Stage 2

Low level fe

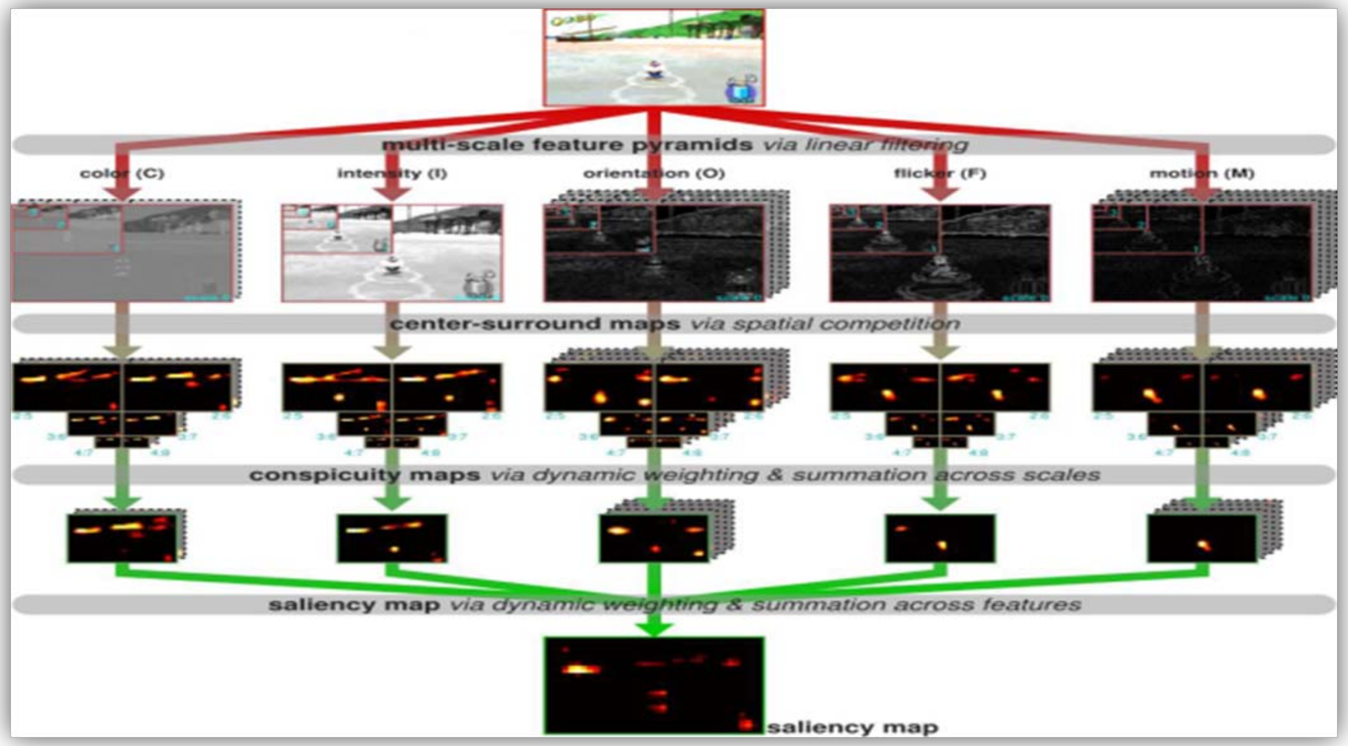
serial, one r

a slow,



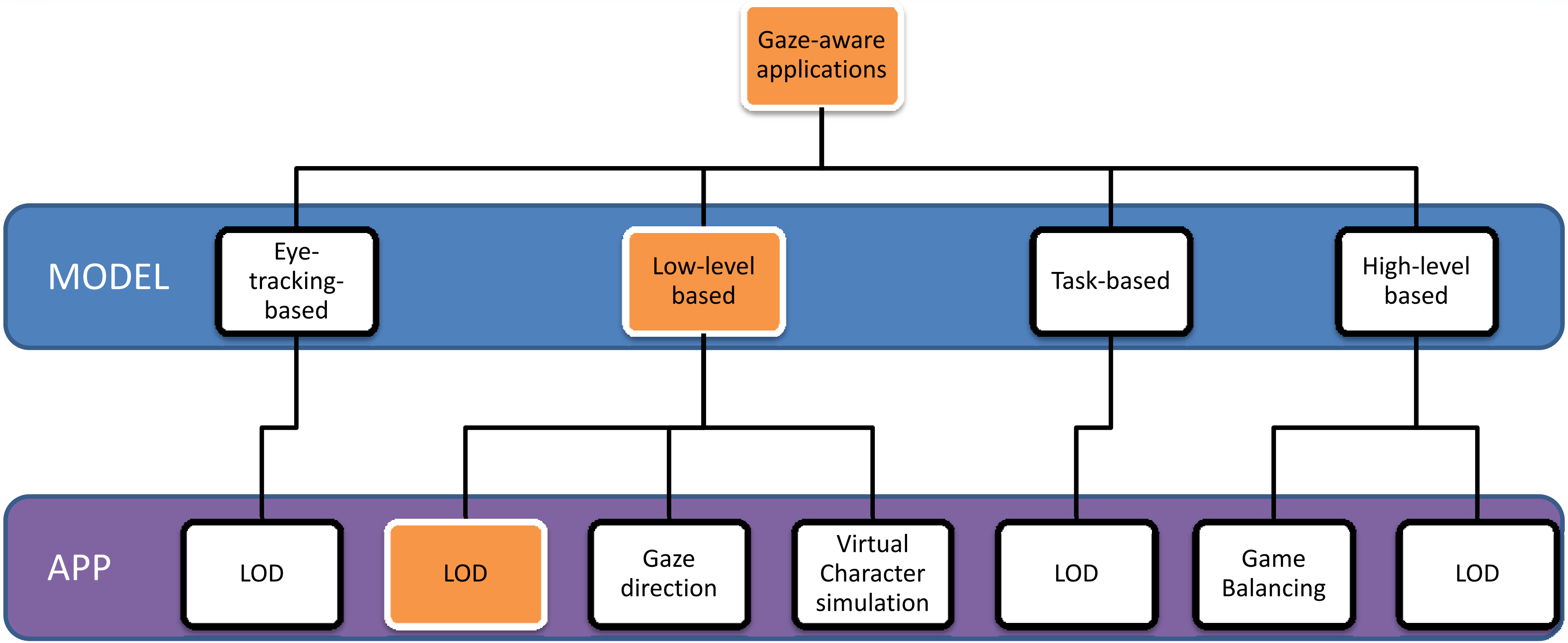
Feature Integration Theory

A computational model



(Itti et al., 1998)

Outline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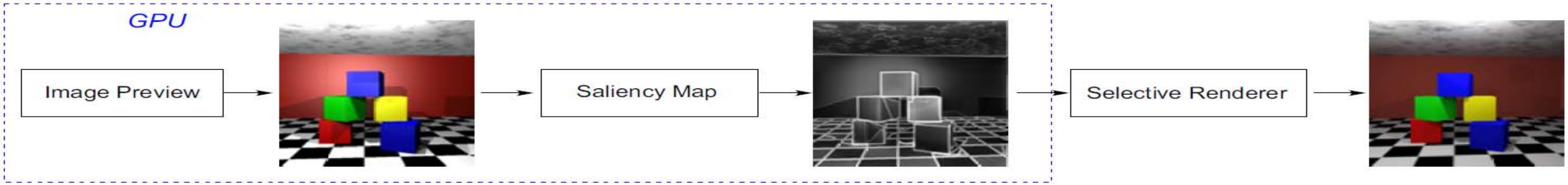
Low-level attention-aware applications

Level-of-Detail

FIT-guided selective rendering often fails

Suffers from low prediction accuracy when

- A Task is being conducted
- High level semantic context properties drive attention **top-down**; e.g. when searching for an object



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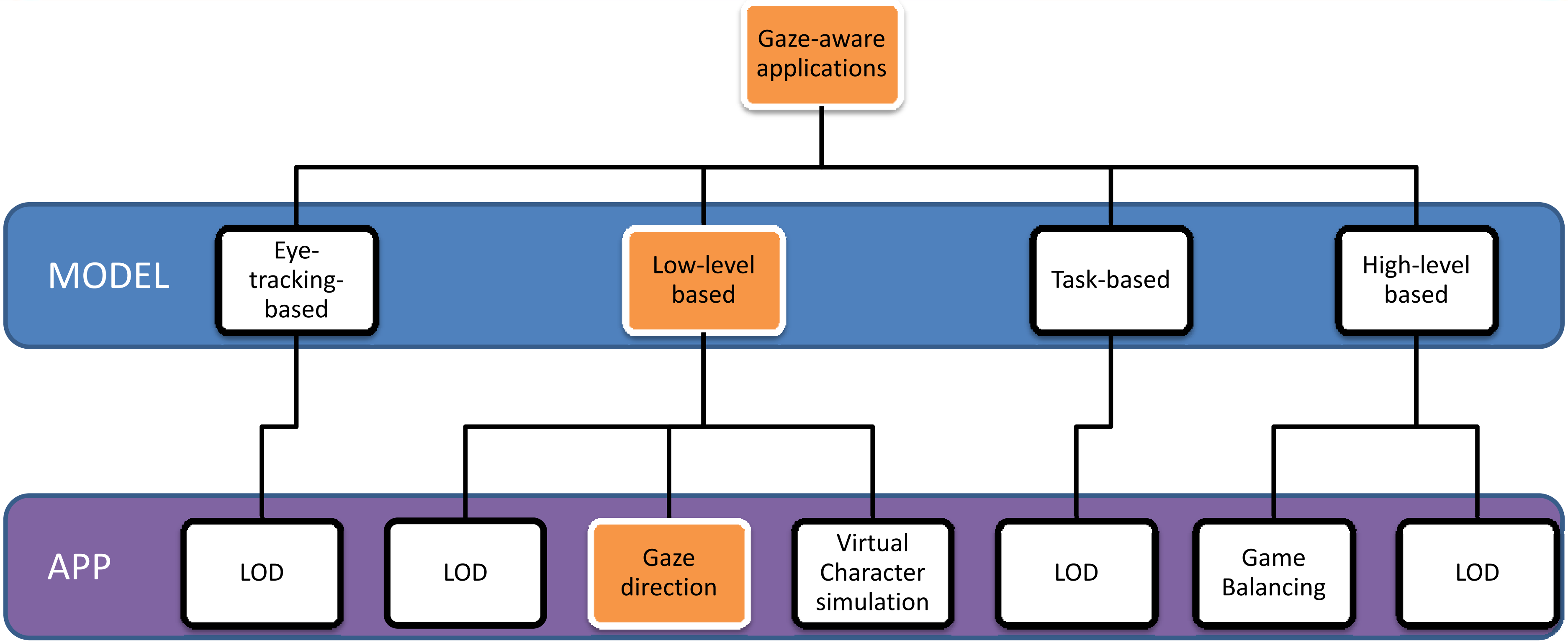
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Gaze Direction

Low-level-based guiding principles

In-game advertising

- The modified item MUST share perceptual features with a target item
- Requires manual 3D-model modifications

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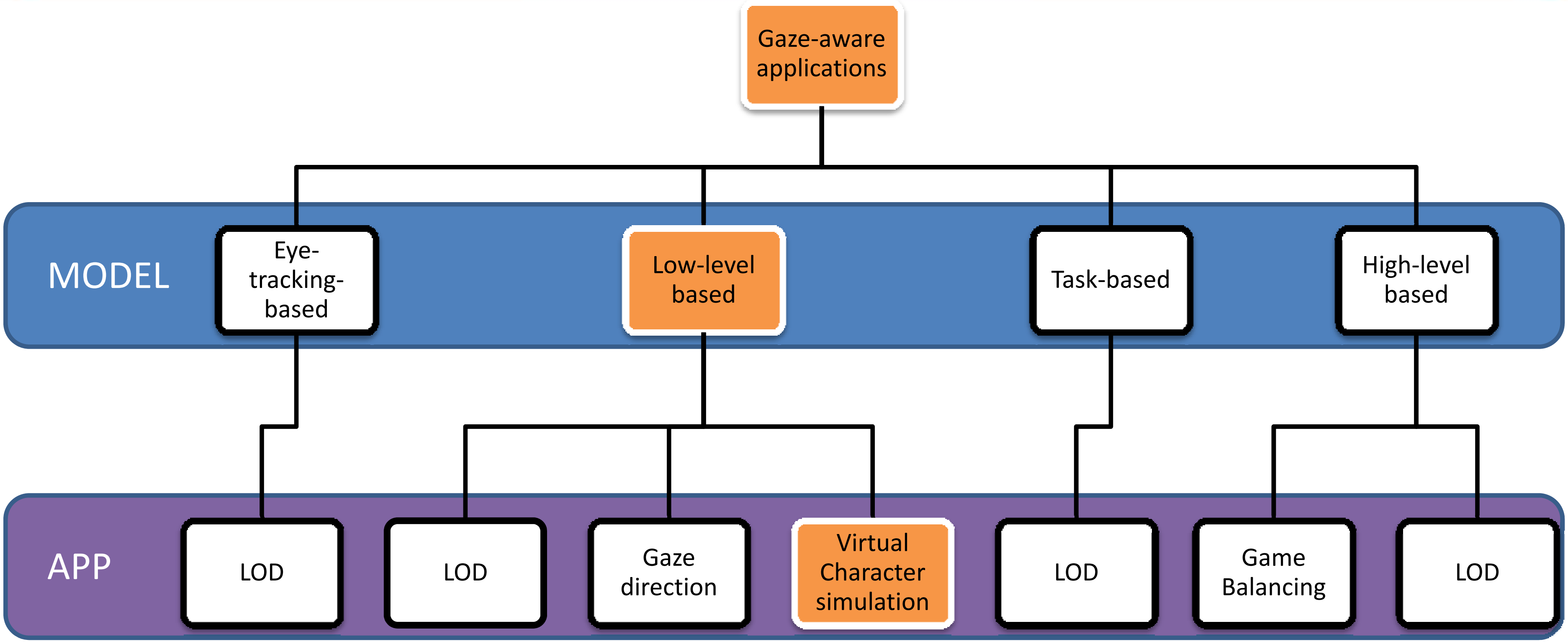
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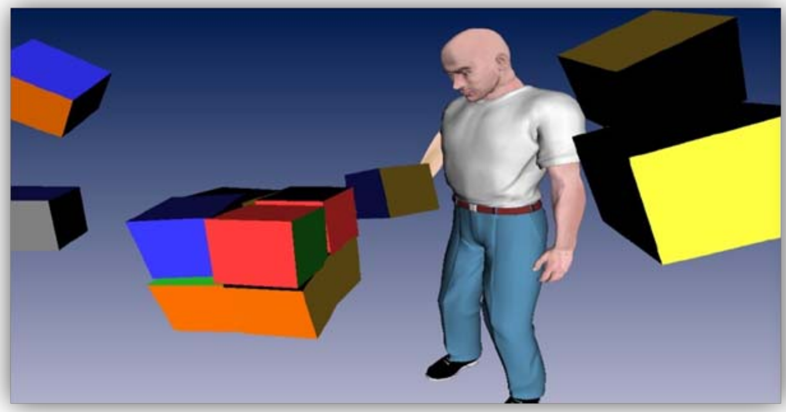
Simulating gaze behavior

Characters and crowds

Simulating gaze behavior

- Limited to low-level salient objects
- Characters and crowds not responding naturally to tasks



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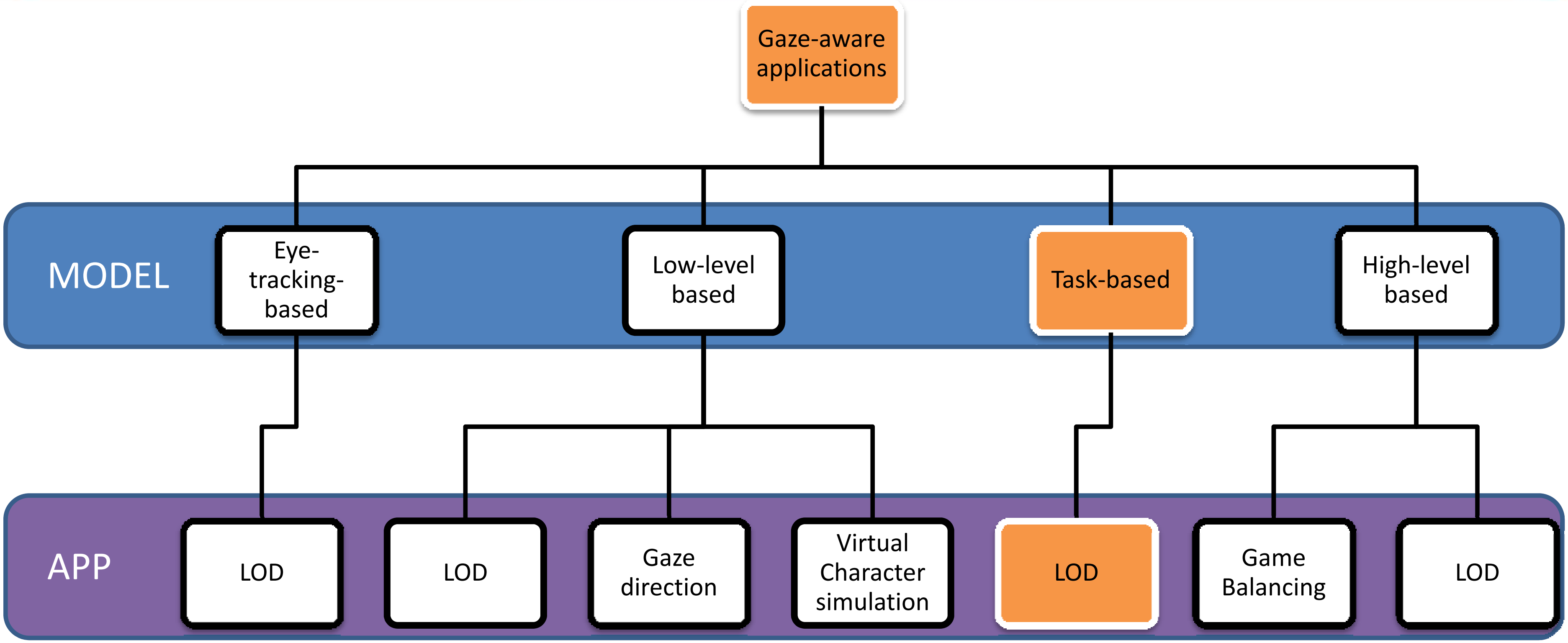
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Task-related Saliency

Saliency based on task demands

Task is predetermined

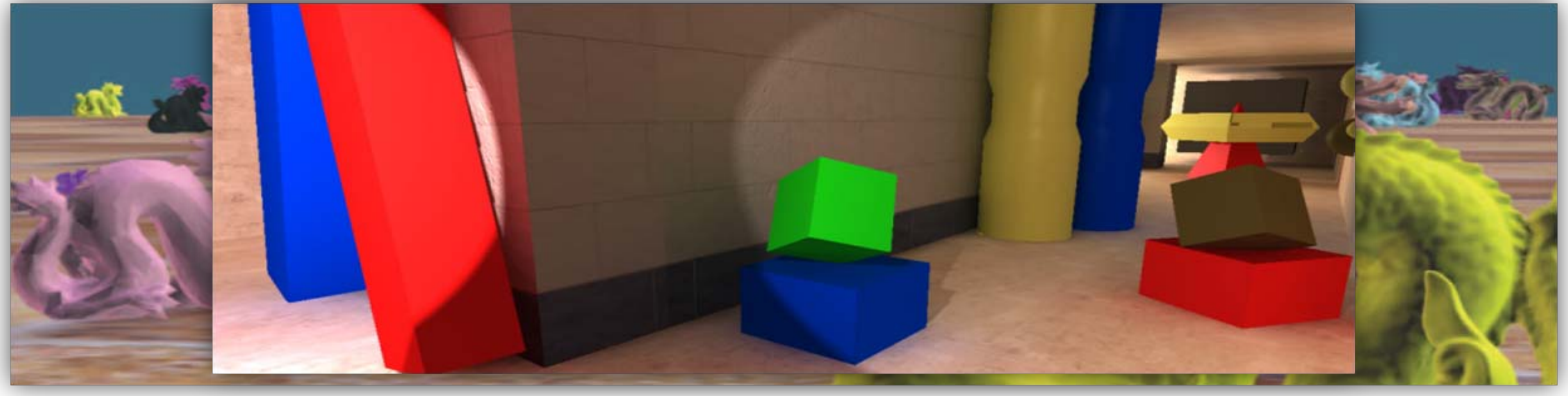
- Task has to be pre-determined
- Approach is limited since it requires labor intensive definition of task restrictions

Task-related Saliency

Combining task-based methods and low level features

Joined low level & task-based methods

- Suffer from the issues of both models
  - Context-agnostic
  - Require manual definition of task restrictions



Thesis Contributions

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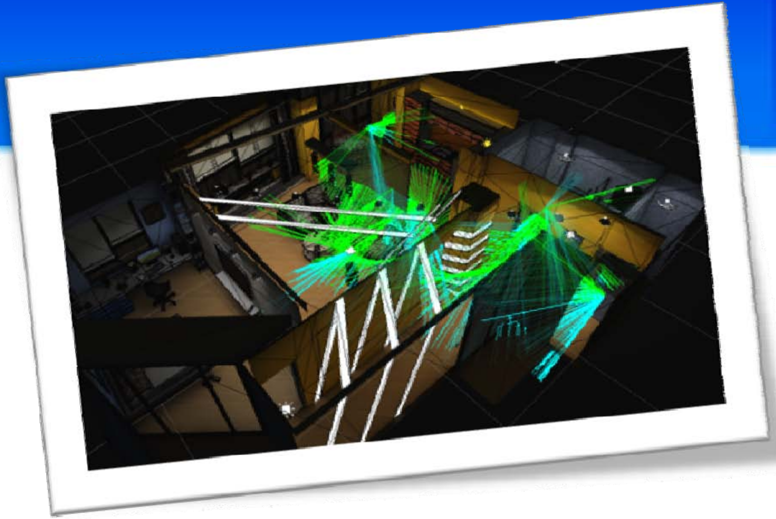

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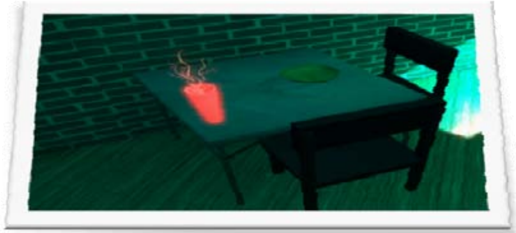

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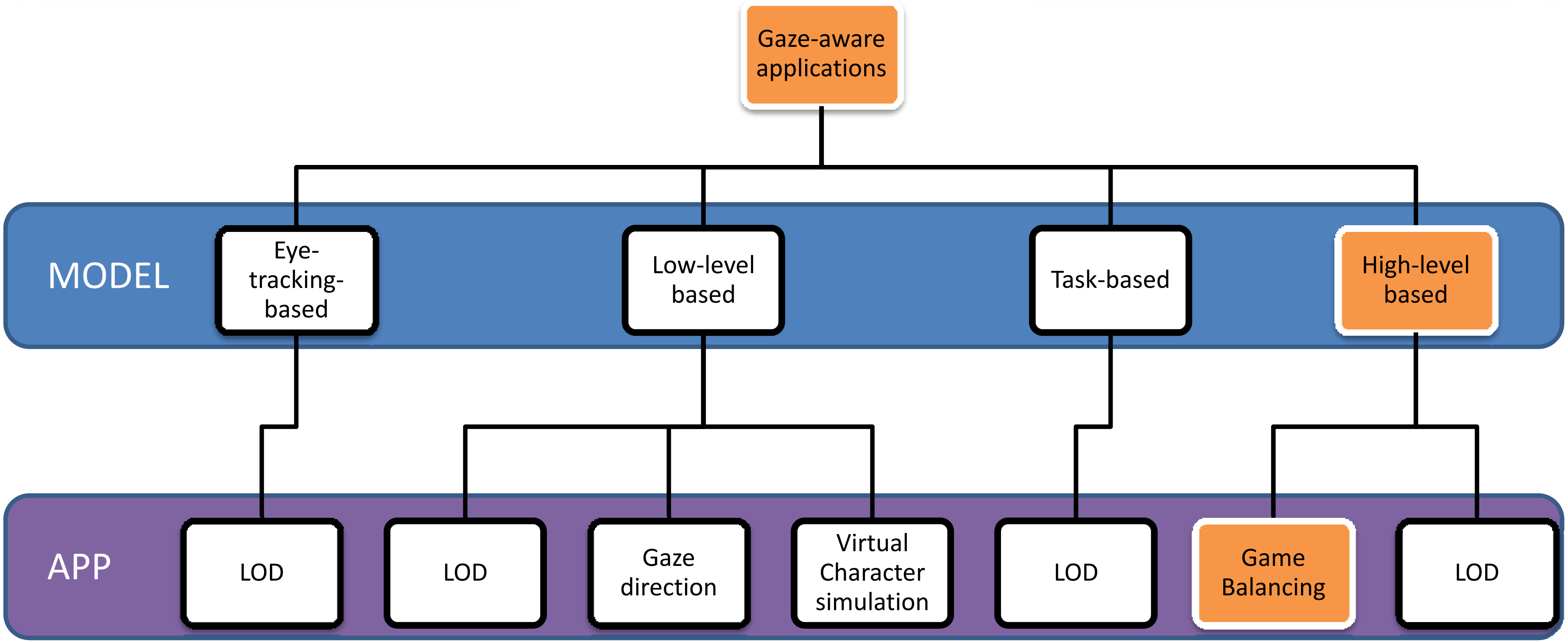
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High Level Saliency

Mapping visual representations to meaning and semantics

A High Level Saliency Predictor

- Our goal is to define a computational model applicable to any context; a challenging task
- When attending a scene, recently acquired knowledge from attentional processing is combined with pre-existing knowledge about a context, e.g. "bedroom"

However!

Until recently a model that explicitly links in a **physiologically plausible** manner high level saliency hypotheses with attention deployment was missing

High Level Saliency

Hypotheses

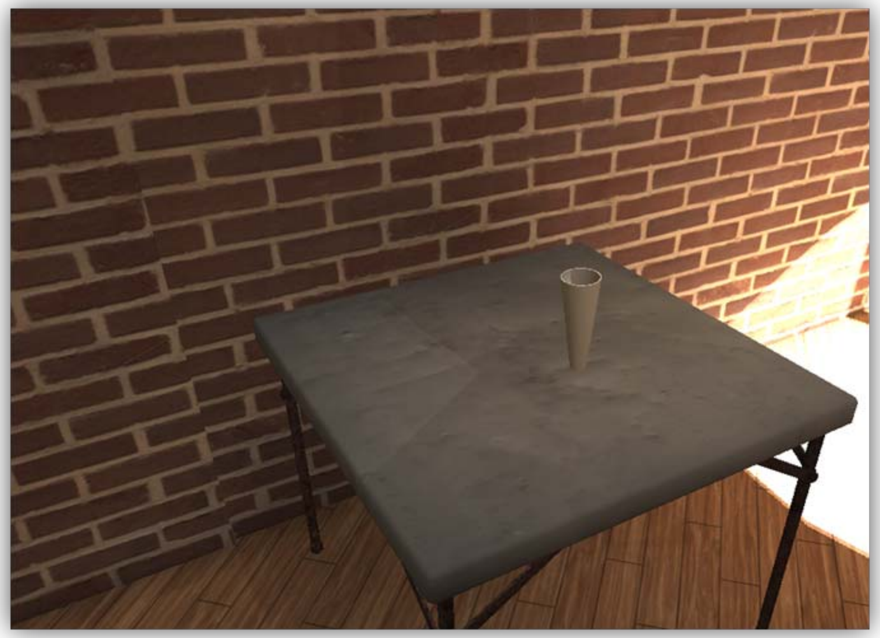
Scene Schemata ***Brewer & Treyens, 1981***

Out-of-context objects are salient

High Level Saliency

Hypotheses

Object Singletoness	***Theeuwes & Godijn, 2002***
Physically isolated objects pop out	



High Level Saliency

Scene schemata & Object singletoness

VIDEO

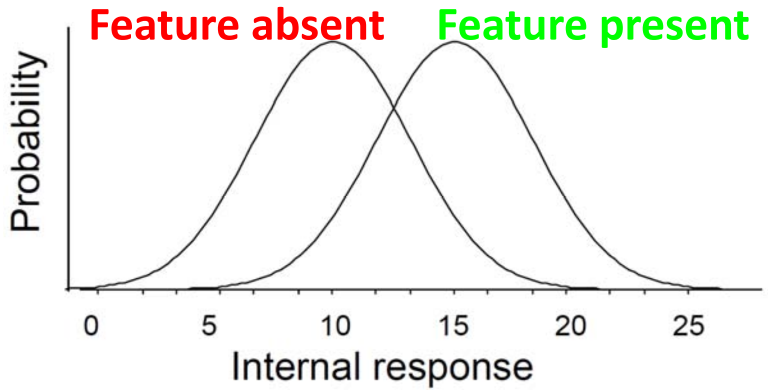
Attentional Processing

The Differential Weighting Model (DWM) *Eckstein, 1998*

A single stage model

- Attentional processing via Gaussian combination rules
- Firing behavior encoded in Bayesian priors
- For every pixel of every frame:

$$LR_{j,x,y,f} = \frac{l_{j,x,y,f}(\lambda_{j,x,y,f}|s)}{l_{j,x,y,f}(\lambda_{j,x,y,f}|n)} = exp\left(\frac{\lambda_{j,x,y,f}d'_j - 0.5d'^2_j}{\sigma^2}\right) \quad (1)$$



Extending the Differential Weighting Model

Defining units for scene schemata and physical isolation states

Extending the Differential Weighting Model

Extending the Differential Weighting Model

Scene schema & physical isolation sensory units

High Level Sensory Units

We extended the original DWM equations to describe two novel high-level sensory units tuned to:

- Schema inconsistencies
- Singleton state of objects

Extending the Differential Weighting Model

Scene schema & physical isolation sensory units

Averaging

We average the components using weights obtained from perceptual studies exploring the effect of High Level hypotheses on task completion time

Viewport *Likelihood ratios* *Saliency*

Perceptual Study

Obtaining experimental data during gameplay

Motivation

We conducted three experiments for three reasons:

- Effect of scene schemata and singletons in VEs unknown
- Empirical classification of objects in scene schemata
- Extension of the DWM requires weighting factors for the two hypotheses

Perceptual Study

Experiment 1

Experiment 1: Classifying objects into schemata

- Empirical classification of scene objects in relation to their surroundings
- 50 objects assessed
- 21 people rated objects using a 7-point Likert scale
  - "How likely for each item is to appear in a given scene?"

Perceptual Study

Experiments 2 & 3

Experiments 2 & 3: Determining the effect of Semantic and Physical Context on task completion time

- Effect of physical and semantic manipulations on task completion time
- Inspired by a real Adventure game
- Search task (Exp. 2): Participants knew exactly what they were searching for
- Non-Search task (Exp. 3): Participants did not know what they were searching for; free exploration of the environment

Perceptual Study

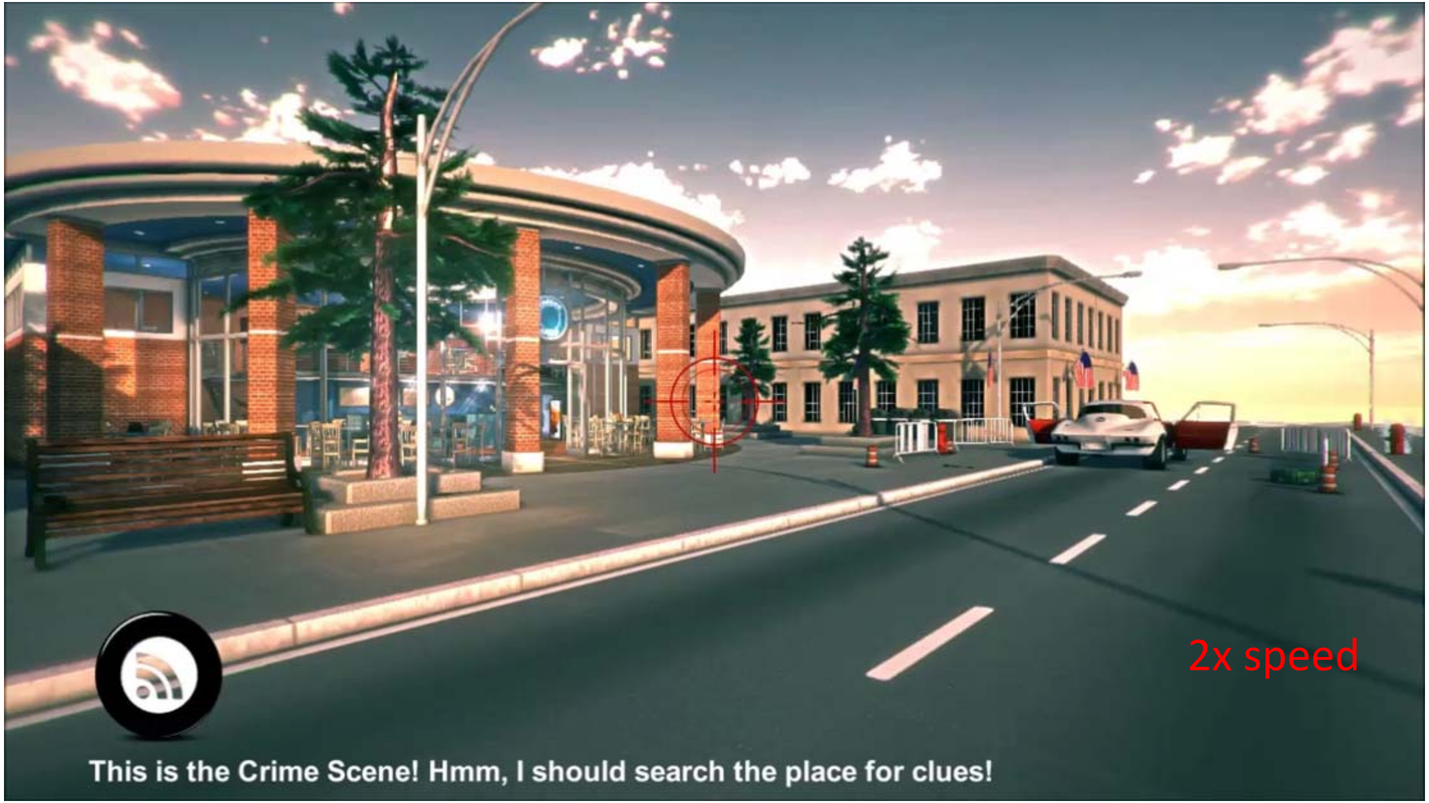
Experiments 2 & 3

Stimuli

- Factorial combination of factors - 4 conditions generated - 2 Tasks
  1. Consistent/Compound
  2. Inconsistent/Compound
  3. Consistent/Singleton
  4. Inconsistent/Singleton
- 80 people, 10/condition

Perceptual Study

Sample Search task

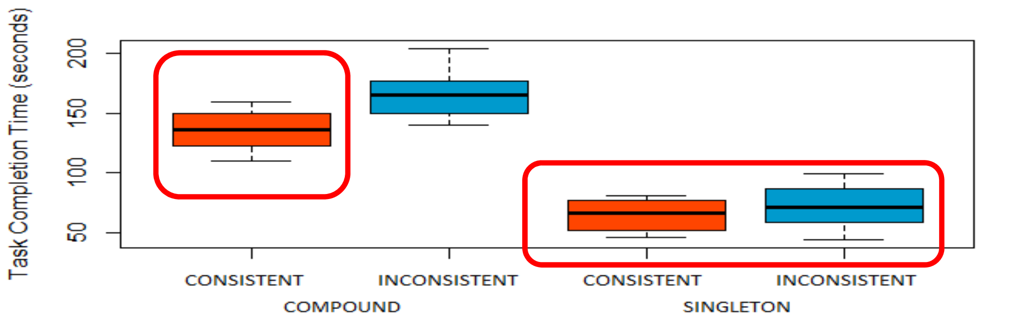


VIDEO

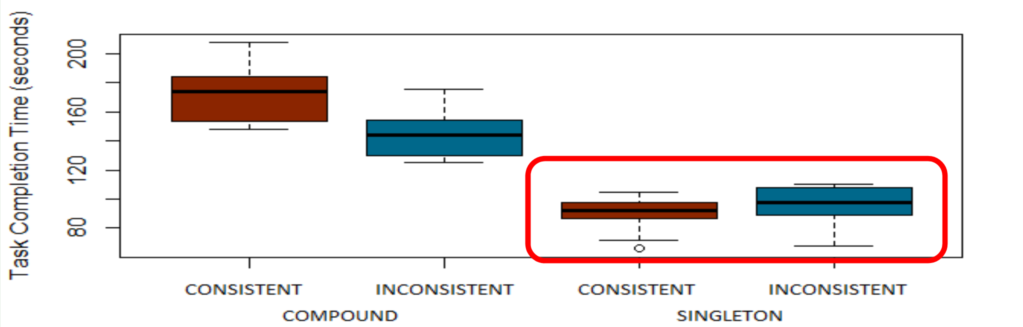
Perceptual Study

Results

Experiment 2: Task completion time distribution in a Search task



Experiment 3: Task completion time distribution in a Non-Search task

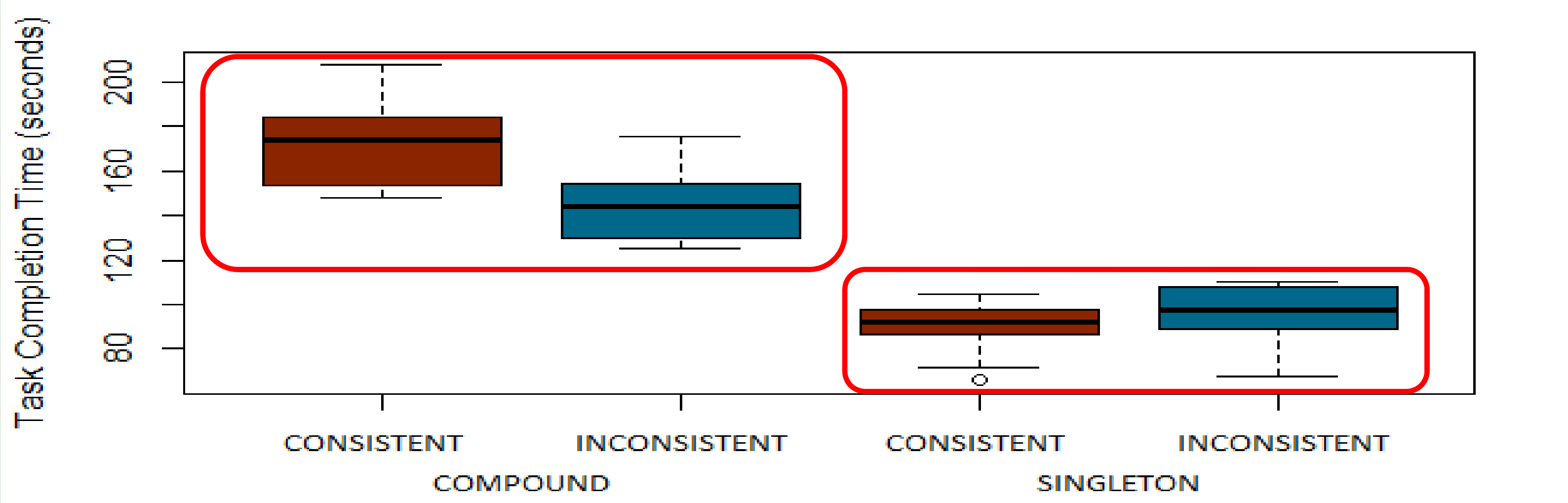


Object consistency decreases task completion time for Search tasks

Perceptual Study

Results

Experiment 3: Task completion time distribution in a Non-Search task



In a Non-Search task, consistency

- Increased task completion time for compound objects
- Decreased task completion time for singleton objects.

Perceptual Study

Weight Generation

Weight Generation via General Linear Modeling

- We subjected the completion times to a Multiple Linear Regression (MLR) analysis
- Generate a quantitative model of how the different experimental factors affect performance
  - Also indicates the relative importance of each factor

Table I The Regression Coefficients and Their Significance on the Overall Model, for the Case of a Search Task

Coefficients	Estimate Time	p-value
Intercept	158.962	<0.0001
+Singleton placement	−81.309	<0.0001
+Consistent placement	−18.381	0.003
+Joint Term	22.190	0.055

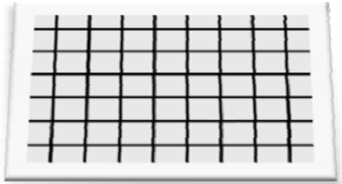
Table II The Regression Coefficients and Their Significance on the Overall Model, for the Case of a Nonsearch Task

Coefficients	Estimate Time	p-value
Intercept	153.008	<0.0001
+Singleton placement	−67.111	<0.0001
+Consistent placement	11.944	0.039
+Joint Term	−32.407	0.025

HLSM: The High Level Saliency Model

GPU based implementation

$$LR_{j,x,y,f} = \frac{l_{j,x,y,f}(\lambda_{j,x,y,f}|s)}{l_{j,x,y,f}(\lambda_{j,x,y,f}|n)} = exp\left(\frac{\lambda_{j,x,y,f}d'_j - 0.5d'^2_j}{\sigma^2}\right)$$



$$\lambda_{semantic} = \frac{c-m}{c} \qquad \lambda_{physical} = \frac{1}{1-c} \times \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Implementation - Stage 1

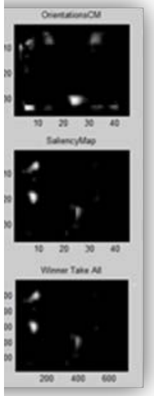
- Compares the scene schema of each object against the scene schemata of the objects surrounding it
- Estimates the number of neighbors for each examined object + available image depth information

HLSM: The High Level Saliency Model

GPU based implementation

Implementati

- Runs on a
- Highlights



High Level Saliency

HLSM: The High Level Saliency Model

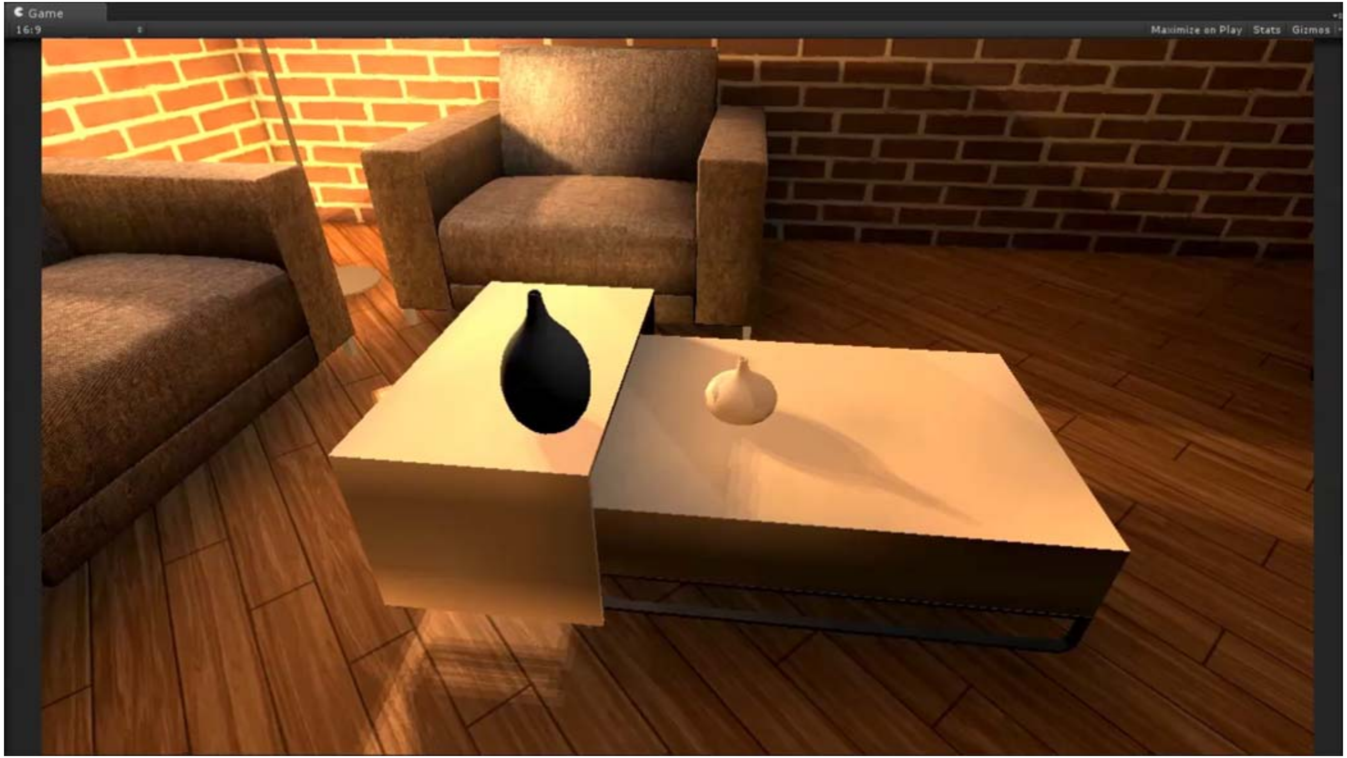
Game Balancing

Game Level Editing

- Looking for an object is a common task in (Action-)Adventure video games
- Plot-critical objects are placed in selected locations to ease or burden the player
- Maintain challenge via Game Balancing
- Aid game level designer to identify object saliency depending on location

HLSM: The High Level Saliency Model

Saliency Detection



VIDEO

Evaluation of Game Level Editing

Experiments 4 & 5: Evaluation of the implementation

Evaluation of the High Level Saliency Model

Evaluate the efficiency of our model in predicting attention deployment by

- Examining its effect on task completion time
- Acquiring eye-tracking data

Evaluation of Game Level Editing

Experiments 4 & 5: Evaluation of the implementation

Design of the Game Balancing evaluation experiment

- Game Levels were designed with the HLSM system
- Four game levels
  1. Easy/Search task
  2. Hard/Search task
  3. Easy/Non-Search task
  4. Hard/Non-Search task
- Three objects in quest for all levels
- Used the already classified objects of Experiment 1
- 40 participants, 10/condition

Evaluation of Game Level Editing

Footage

VIDEO

Evaluation of Game Level Editing

Completion time & Eye-tracking data Analysis

Completion time Analysis

- Both tasks completion times were reduced for the easy tasks vs the hard tasks
- Consistent with analysis of Experiments 2 & 3

Eye-tracking data Analysis

Clear influence of both context consistency and physical isolation in attention deployment

Evaluation of Game Level Editing

Eye-tracking Data Heat maps

Aggregated fixations over raw eye data from all participants and visual angles

Search task: *Spectacles* ***Non-Search task:*** *Items for a car trip*

Heat map analysis

- In a Search task eye gaze is directed to consistent object locations
- In a Non-Search task the eye scan pattern spans over the entire scene

Summary

Conclusion & Future Work

Conclusion

- Successful prediction of salient objects identified as non-salient in terms of low level features
- We validated our model's performance via eye-tracking
- Implicitly adjust game level difficulty by manipulating object topology

Summary

Conclusion & Future Work

Limitations

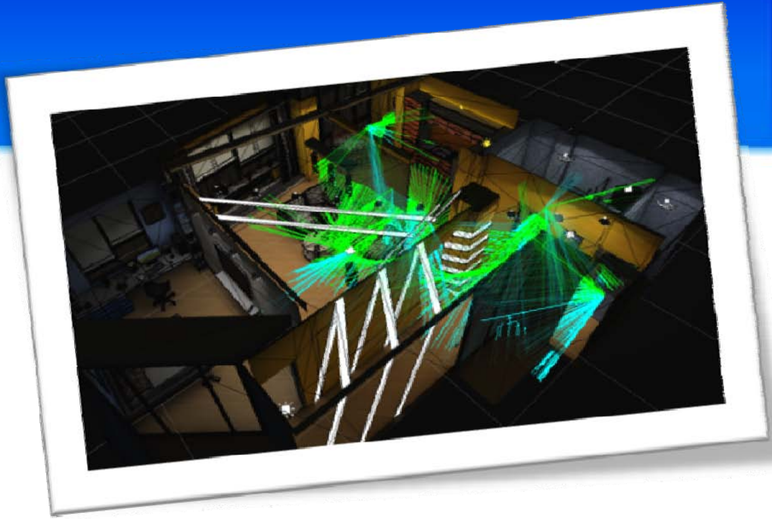
Only two contextual factors are integrated in this model; more can be found in the cognitive psychology literature

Publications

Koulieris, G.A., *Drettakis, G., Cunningham, D., Mania, K. (2014, September). An Automated High Level Saliency Predictor for Smart Game Balancing. ACM Transactions on Applied Perception (TAP) 11, 4, Article 17, 21 pages.*

Koulieris, G.A., *Drettakis, G., Cunningham, D., Mania, K. (2014, July). High level saliency prediction for smart game balancing. In ACM SIGGRAPH 2014 Talks, p. 73.*

Overview



Motivation

Problem Statement

Contributions

Background

Part 1: An Automated High-Level Saliency Predictor for Smart Game Balancing

Part 2: C-LOD: Context-aware Material Level-of-Detail applied to Mobile Graphics

Part 3: Gaze Prediction using Machine Learning for Dynamic Stereo Manipulation

Summary