Evaluation of C-LOD
Model Efficiency

VIDEO

Summary
Evaluation and Conclusions

Conclusions

- **Extended the High Level Saliency Model with 4 new factors**
- Acquired weights to train our model from a perceptual study
- C-LOD identifies observed object **8 times** better than random
- Prediction rate 90% for 3 attended objects
- With C-LOD
  - Complex effects omitted in mobile devices can now be employed
  - More stable frame rate
  - Improved battery life (6.5% increase) due to reduced GPU utilization

Summary
Conclusion & Future Work

Limitations

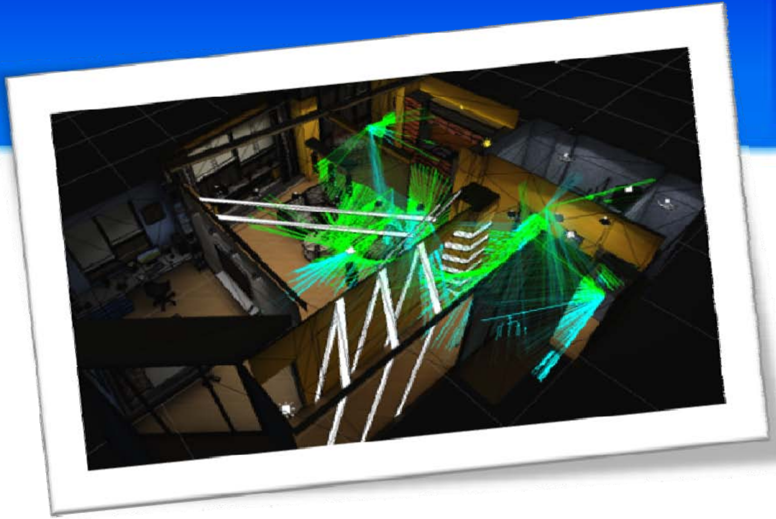
Semantic tagging information for each 3D-model is required for the model to work

Publications

Koulieris, G.A., *Drettakis, G., Cunningham, D., Mania, K. (2014, July). C-LOD: Context-aware Material Level-of-Detail applied to Mobile Graphics. In Computer Graphics Forum Vol. 33, No. 4, p. 41-49.*

Koulieris, G.A., *Drettakis, G., Cunningham, D., Sidorakis, N., Mania, K. (2014, July). Context-aware material selective rendering for mobile graphics. In ACM SIGGRAPH 2014 Posters, p. 92.* ***[won 3rd place at the ACM Graduate Student Research Competition]***

Overview



Motivation

Problem Statement

Contributions

Background

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

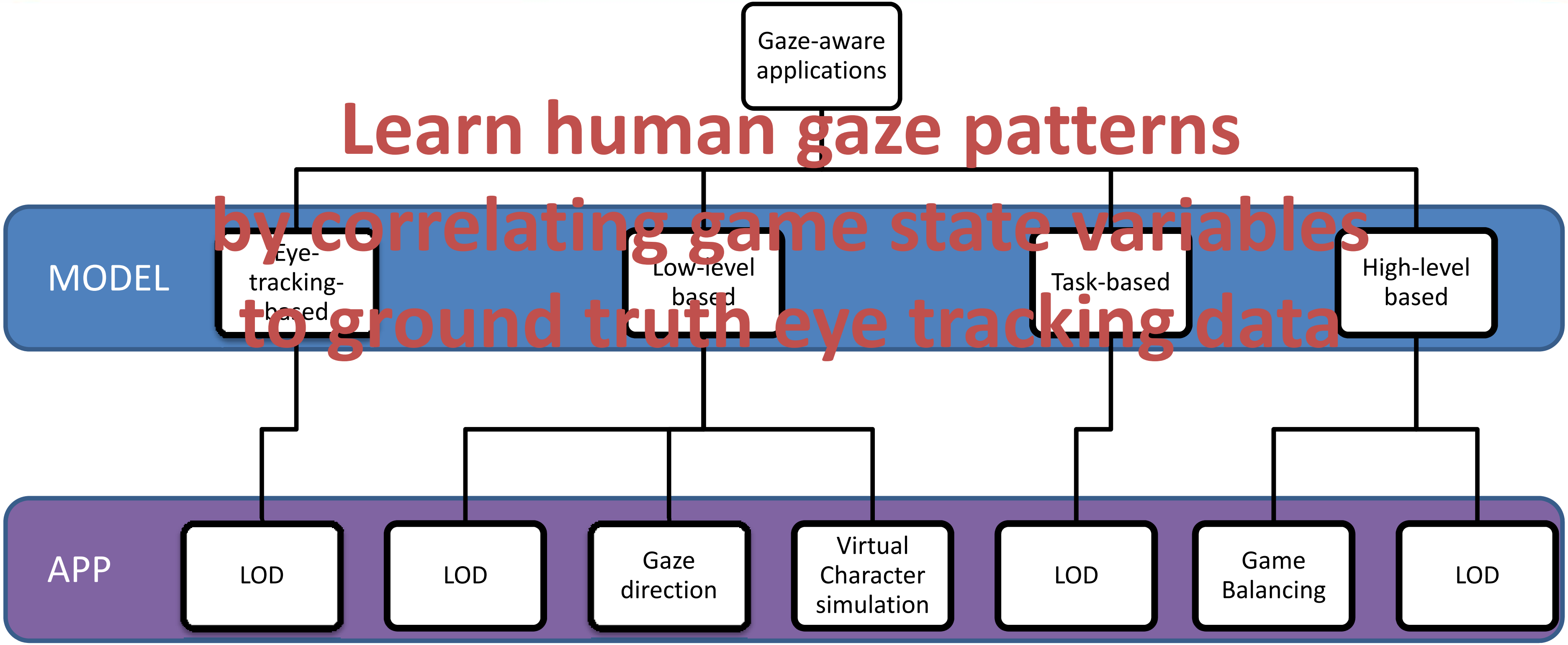
Part 2: C-LOD: Context-aware Material Level-of-Detail applied to Mobile Graphics

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

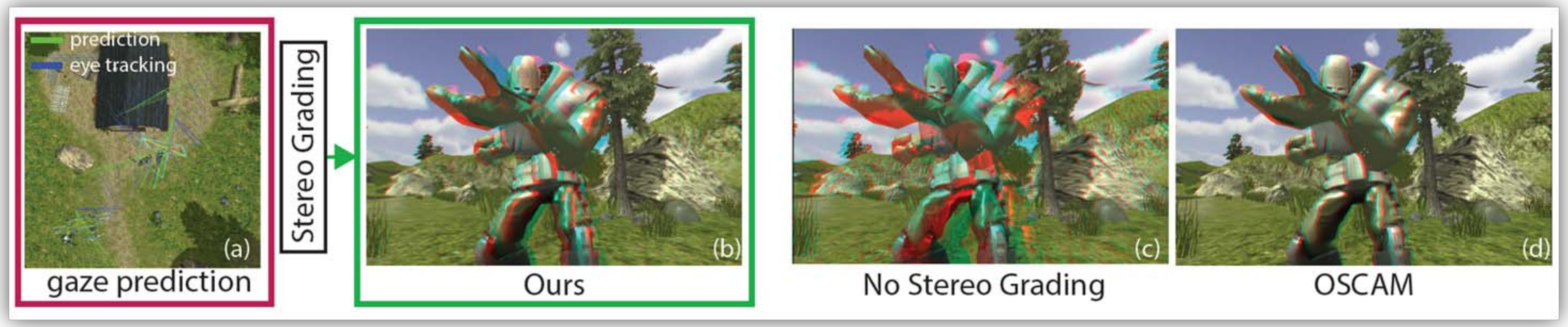
Summary

Outline

Learn human gaze patterns by correlating game state variables to ground truth eye tracking data



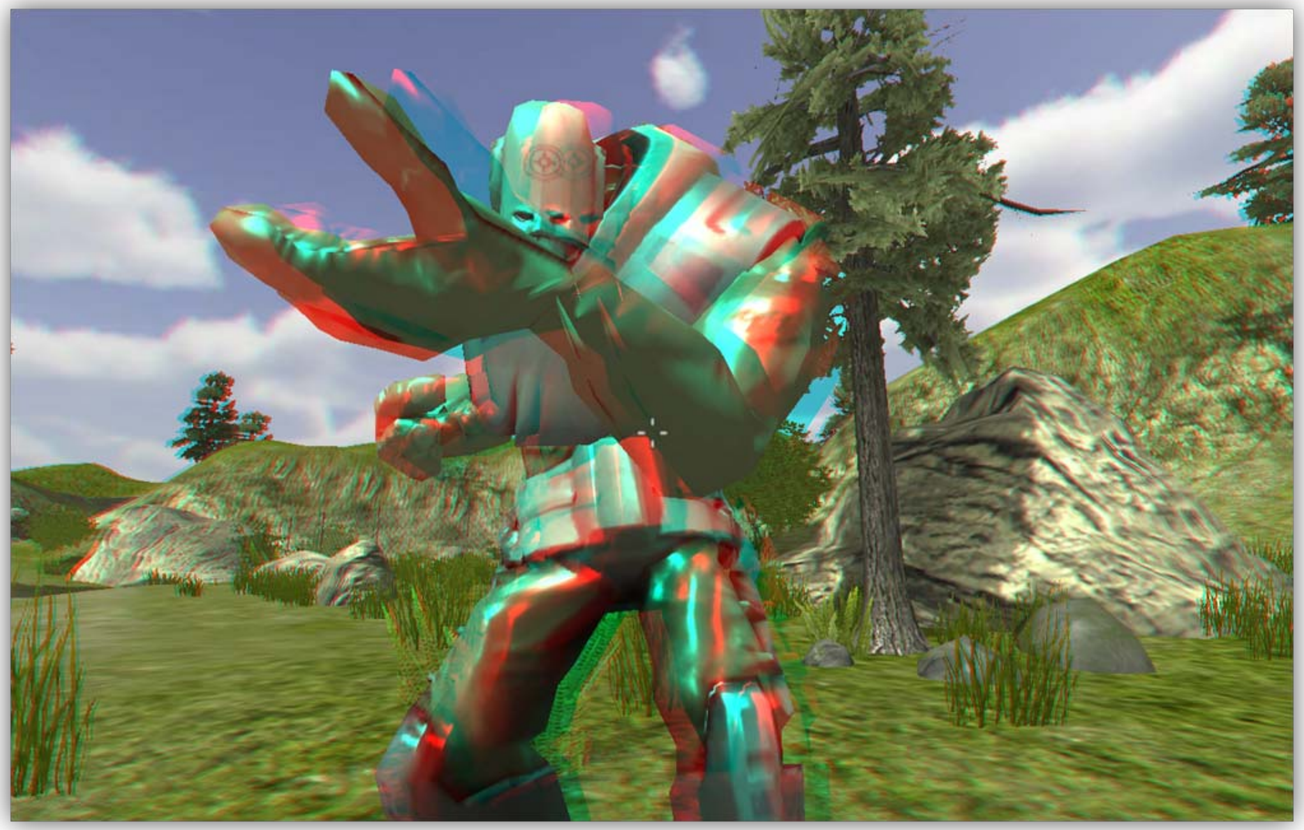
Introduction
At a Glance



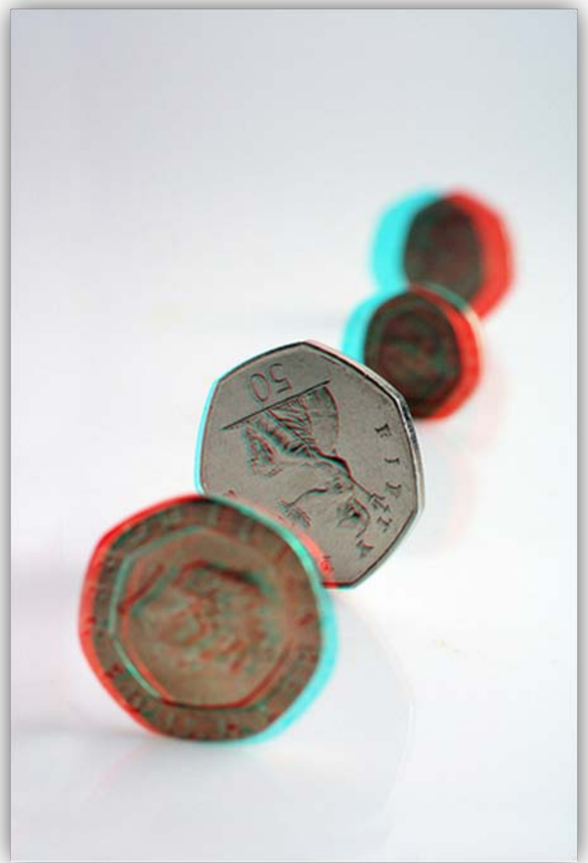
We achieve

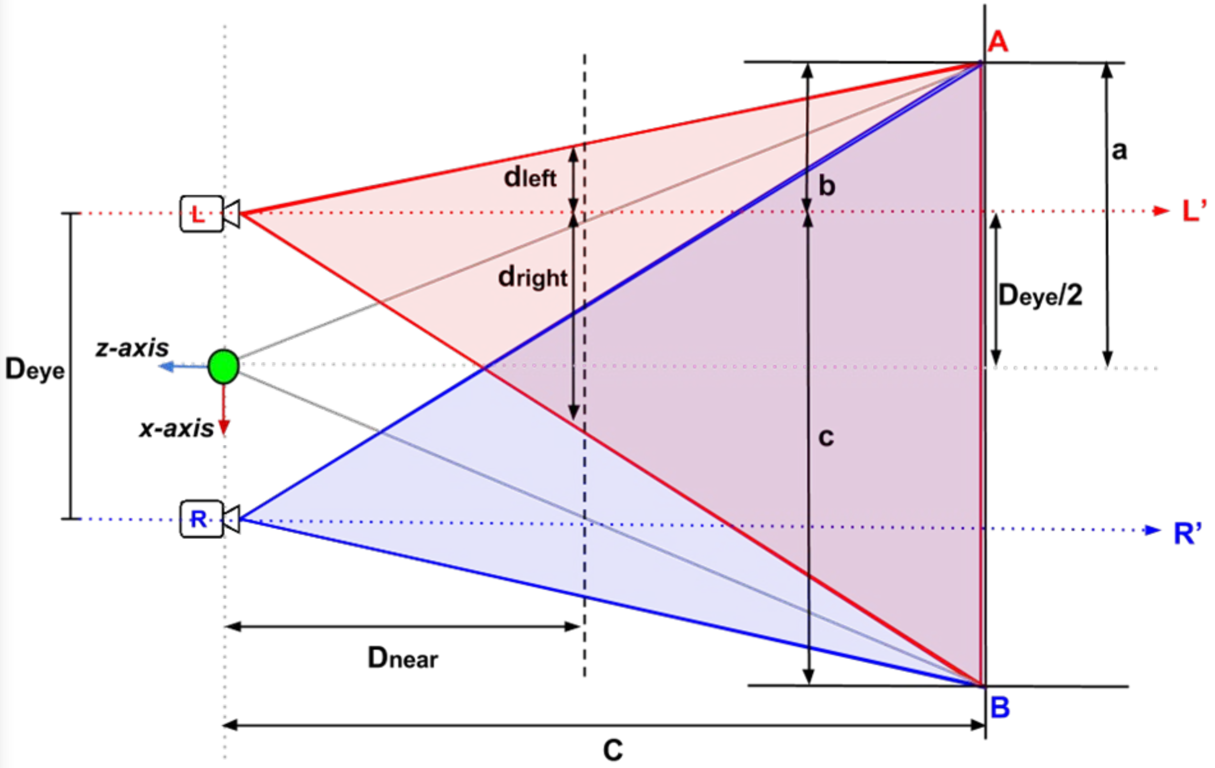
1. Effective real-time gaze prediction based on Decision Forests without manual object tagging
2. Dynamic, comfortable stereo grading without cardboarding effects

Introduction
Multiplexing a stereo pair



Introduction
Positive & Negative (crossed) Disparity





Introduction
Motivation

Automatic gaze prediction

- Account for task
- Avoid manual categorization of objects

Learn from actual gaze data!

Related Work
Machine Learning

Decision Forests in Games

- AI opponents
- Level Generation
- Game Balancing
- Motion recognition

Never been used for attention prediction in interactive VEs!

- Decision Forests provide powerful multi-label classification
- Employ Decision Forests to learn the correlation of Game State Variables and Gaze

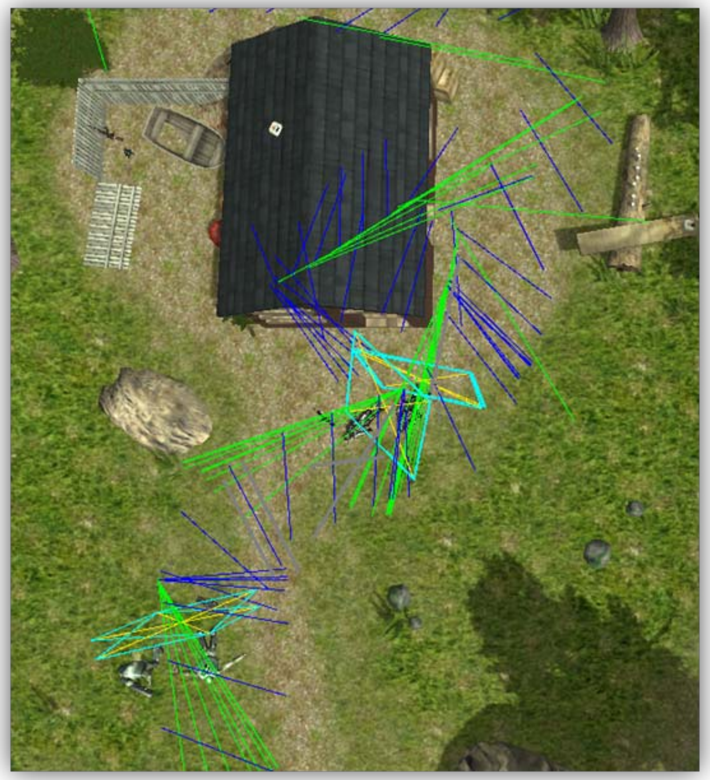
Related Work
Video Game State Variables

Game structure

- Relationships between game objects and player actions define the game structure
- Game structure is represented in the source code via variables
    - e.g. Vectors indicating player location or distance from an enemy

The value of these variables influences player behavior!

Attention Model
3-step procedure



Identify important game variables and object classes

Data Collection

Classifier Training

Attention Model
Identifying important variables

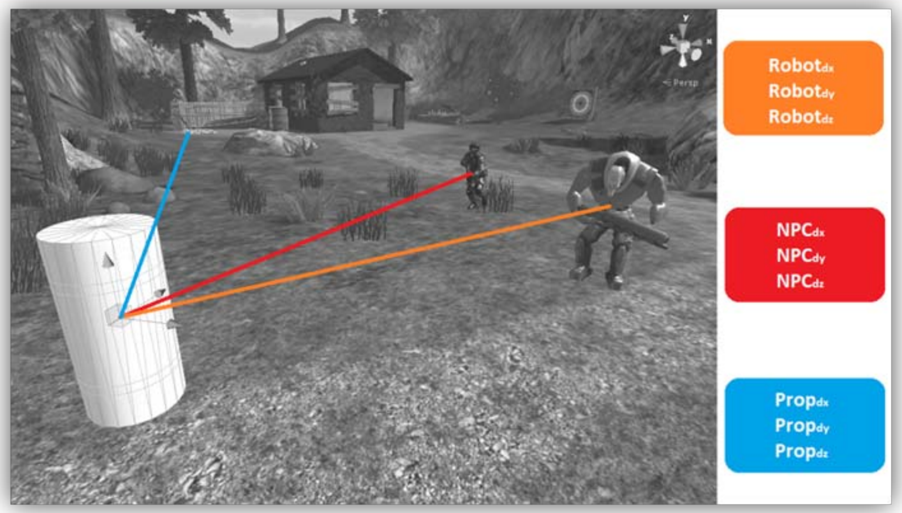
Measuring variable variation

- Variable range
- High pass filter on variable derivatives
- **Run on all internal variables as well as agent location/distance AI variables**

Selecting variables

- Initially, more than 300 game state variables
- Dimensionality reduction: Ignore variables with little variability
- **We kept ~5% of the variables (13)**

Attention Model
Identifying important variables



Prop$_{dx}$	Robot$_{dx}$	NPC$_{dx}$	Health	Ammo
Prop$_{dy}$	Robot$_{dy}$	NPC$_{dy}$	Hunger	
Prop$_{dz}$	Robot$_{dz}$	NPC$_{dz}$	Thirst	

The most informative variables that were selected for data collection. dx, dy, dz variables denote distances from the object.

Attention Model
Identifying object classes

Parsing game scene hierarchy

- Automatically parsed a set Λ of object categories or *class labels*
- Exploit standard naming conventions of 3D models
  - Identifier - Modifier - Variant - Footprint - Optical Distinction
  - “Tree - broadLeaved - 01 - 2x2 - Green”

FallenLog	Boat	WoodFence	Fence	Can
Ammo	Barrels	Brickhouse	Crate	Door
Rock	Tree	Water Pickable	Woodboard	Pond
Platform	Elevator	Robot	Soldier	Bush
Zombie	Mine	Food Pickable	Gun Pickable	

Automatically extracted class labels

Attention Model
Data Collection

Participants of Data Collection phase

- 10 people (2 female, mean age 25)
- Experienced First Person Shooter gamers

Apparatus used for Data Collection

nVisor SX111 HMD with eye tracker

Attention Model
Data Collection

Stimuli used during Data Collection

- 60-90 seconds real gameplay, 20-minute sessions
- Reach the flaming spaceship. Avoid
  - Robots
  - Soldiers
  - Zombies
  - Mines

Data collected (speed-based 5-15 Hz)

13 Variable Samples

<>

Class label fixation

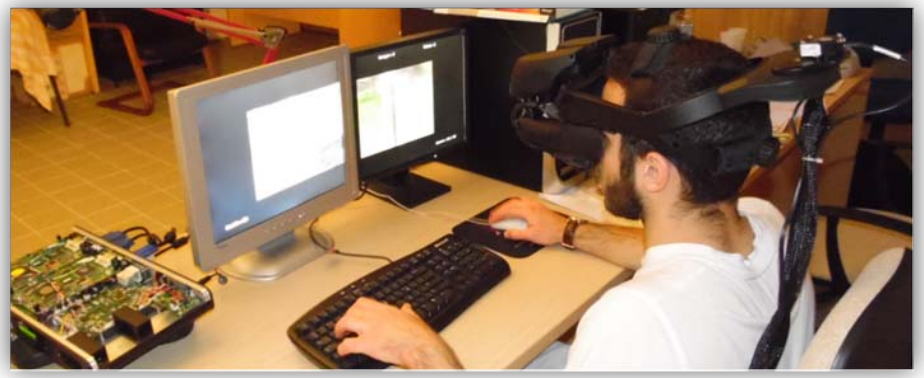
Attention Model
DF Generation and Training

VIDEO

Attention Model
DF Generation and Training

Training data in the database

- Training data set T
- N samples of M=13 features, T = $(X_1, y_1), (X_2, y_2), \ldots, (X_N, y_N)$
- Each record in T includes an input feature vector, $X_i = x_{i1}, x_{i2}, \ldots, x_{iM}$ and the object class label y_{i2} indicated by the eye tracker at the specific moment that sample X_i was taken.



Attention Model
DF Generation and Training

Frequent classes under-sampling

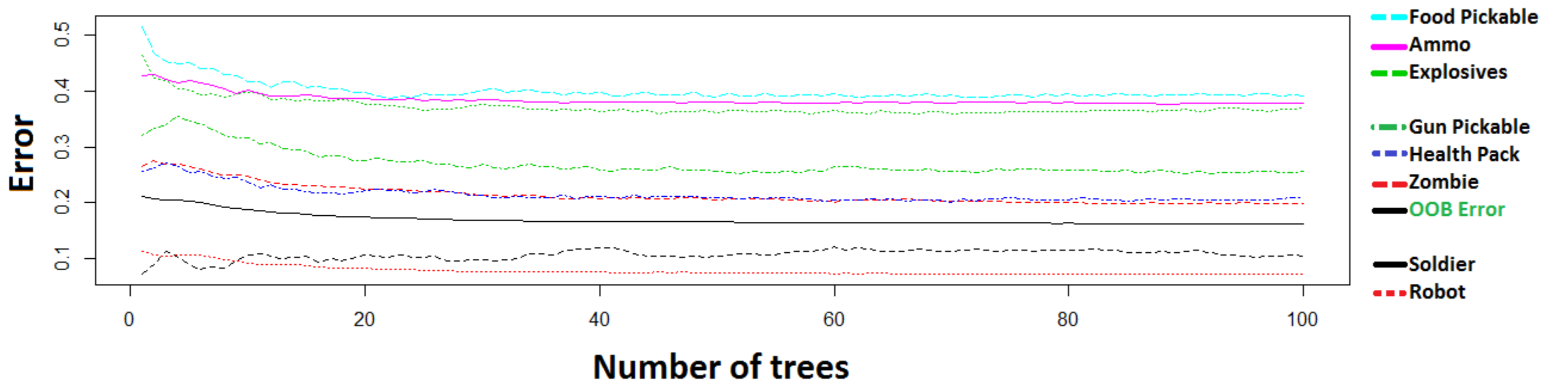
- Class imbalance issue
- More fixations on moving objects
- Avoid high accuracy only for frequent classes

We under-sampled frequent classes!

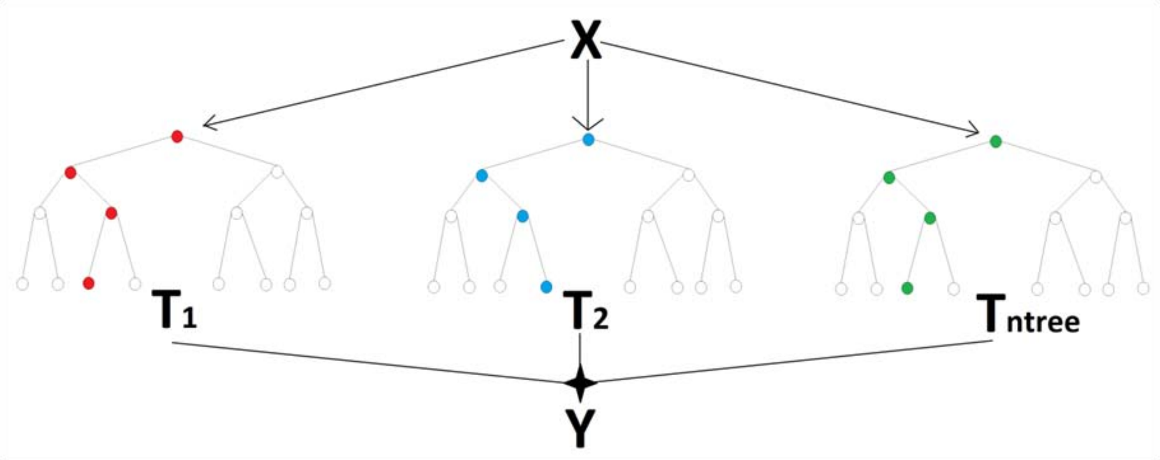
Attention Model
DF Validation and Tuning

Out-of-Bag Estimates: Keeping part of the dataset for validation

- **T' balanced set, spanning N = 55151 samples x M = 13 features + Class**
- Optimized dataset has object categories for which > 55% prediction rate was achieved
- 8 object categories exceed this threshold, **average error 13,26% for 100 trees**
- Objects encountered less frequently have higher prediction error rate



Attention Model
DF Validation and Tuning



Robot	Soldier	Zombie	Health Pack
7.1	11.2	19.9	20.9
Gun Pickable	Explosives	Ammo	Food Pickable
25	36.3	37.8	40.6

Prediction error rate for each object category.

Gaze-based Dynamic Stereo Grading

Manipulating disparity based on attention

Searching for predicted objects in the Field of View

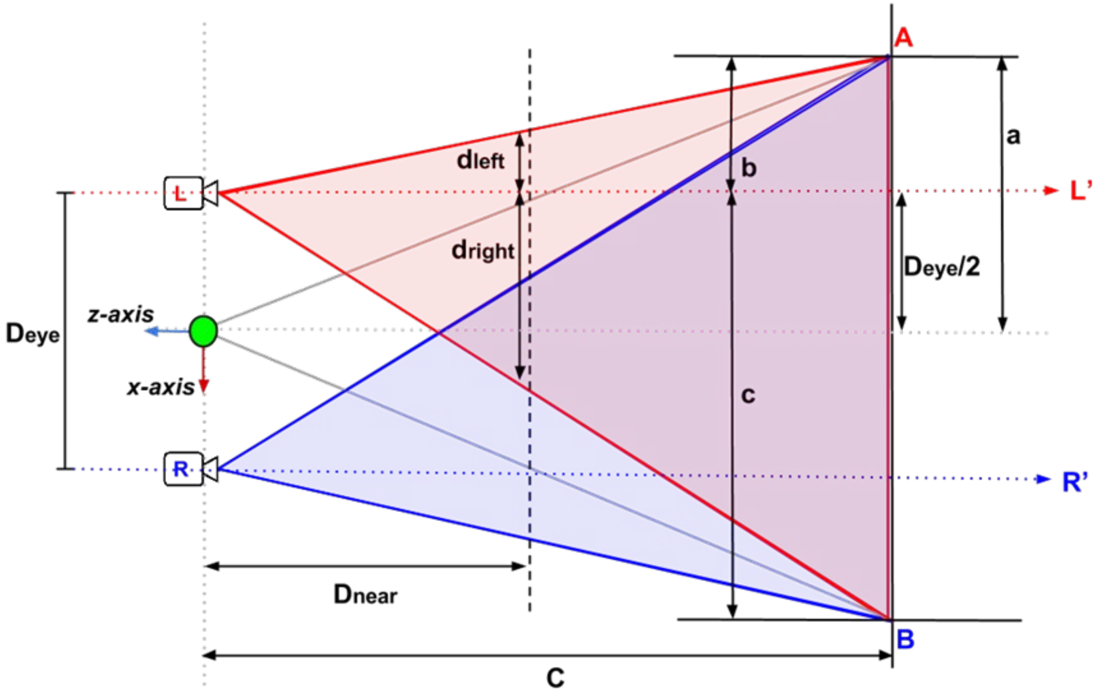
- Find all **visible** objects of the predicted category
  - 1 object found
    - Shift zero parallax plane close to object barycenter
  - >1 objects found
    - Shift zero parallax plane close to combined object barycenter
  - 0 objects found
    - FAIL: Shift zero parallax plane close to the largest object adjacent to frustum center

Gaze-based Dynamic Stereo Grading

Manipulating disparity based on attention

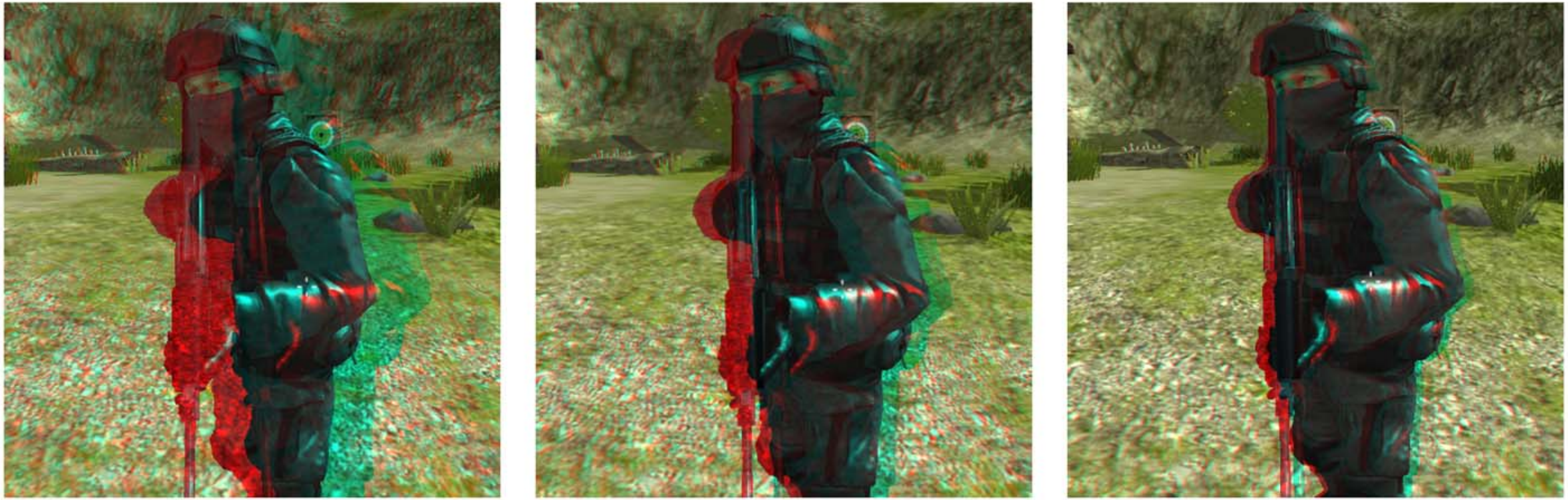
In the comfort zone!

- Place predicted objects in the comfort zone, close to the zero parallax plane (virtual screen)
- Linearly interpolate camera separation and asymmetric frustum parameters
- **2 object queries/second**



Gaze-based Dynamic Stereo Grading

Examples



No display management | Ours | OSCAM

Left to right: No display management, Ours, OSCAM. Please use red/cyan anaglyph glasses; best viewed on a monitor.

Attention Model
Model at work

VIDEO

Attention Model
Model at work

VIDEO

Gaze-based Dynamic Stereo Grading
Optimizations

Optimizations

- More aggressive when grading negative disparities (objects closer than the physical screen)

When objects are closer than 3% of the distance of the virtual camera pair to the virtual plane

Evaluation and Results

DF-predictor and Stereo Grading assessment

Experimental Validation of the DF Predictor & Stereo Grading Method

1. DF-predictor, compare it to a Low Level Saliency Predictor
2. Measure perceived quality of stereo grading in terms of depth and eye strain

3 pair-wise experimental sessions

- Standard <> Our method
- Our method <> OSCAM
- OSCAM <> Standard

10-minute break between sessions to reduce eye strain

Evaluation and Results
Experimental setup

Each session of the experiment

- 10 pairwise 10-second game rounds of gameplay
- 200 seconds in total (10 pairs x 2 conditions x 10 seconds)

Full of *disparity events*

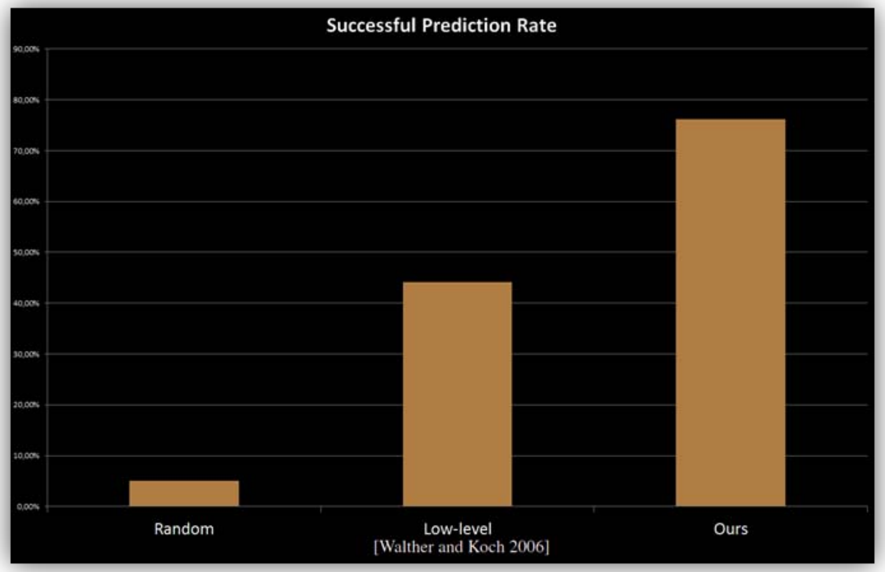
Evaluation and Results
Experimental setup

VIDEO

Evaluation and Results
DF-predictor vs Low Level Predictor

Test-time evaluation of DF-predictor

- DF-predictor already evaluated in terms of OOB error
- **Now validated via eye tracking and compared to state-of-the-art Low Level Predictor**



Evaluation and Results
DF-predictor vs Low Level Predictor

Comparison of low level gaze prediction (middle) and our DF predictor (right) for the same scene (left). The player is threatened by the soldier.

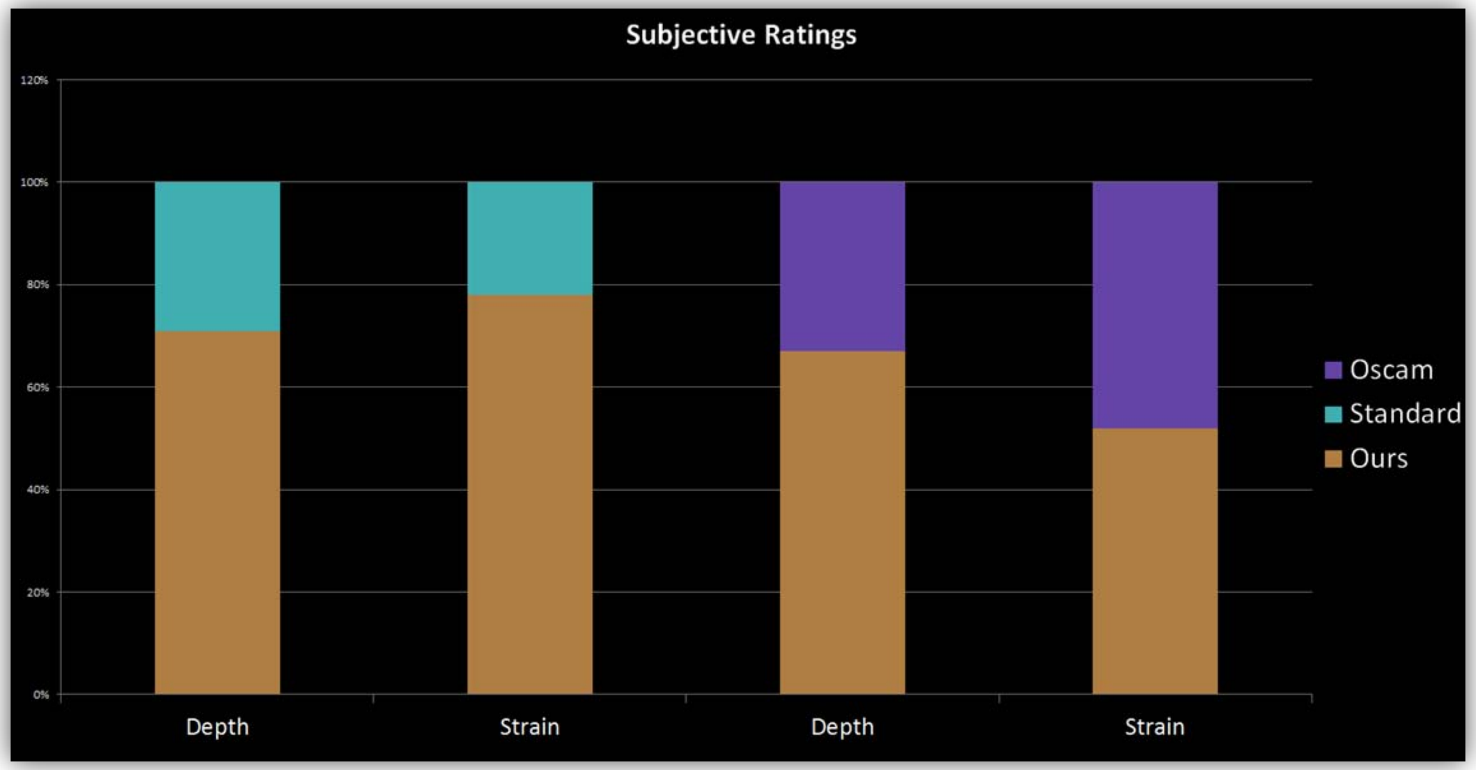
Evaluation and Results
Dynamic Disparity Management

Stereo Manipulation Assessment Protocol

- Inspired by standard Stereo Disparity assessment Protocols
- At the end of each pair in a session, participants were asked to choose between the two sequences of a given pair, to determine
  1. Which one had more **depth**
  2. Which was more **comfortable** in terms of diplopia and eye fatigue

We received 600 answers in total (2 questions x 3 sessions x 10 conditions x 10 participants)

Evaluation and Results
Dynamic Disparity Management



Summary

Gaze-aware Stereo Disparity Manipulation

Contributions

- Our predictor
  - Yields high prediction success rates
  - Is automatic avoiding the need for manual tagging of objects
  - Supports object motion in contrast to previous task-based and high level approaches
- Our localized stereo grading approach
  - Provides better perceived depth than previous global methods
  - While maintaining similar levels of viewing comfort

Summary

Gaze-aware Stereo Disparity Manipulation

Limitations

- The speed of the classifier is low (2 queries/second); a more optimized implementation of DFs' would improve this speed
- The training phase required an eye-tracked HMD; the typical cost of such a setup is probably a realistic option for a game-studio, however, a desktop eye tracker could be used as well

Summary
Gaze-aware Stereo Disparity Manipulation

Future Work

- We expect that a trained instance of the model may be extended to the other levels of the same game or different games with similar mechanics
- If prediction becomes faster, it could be used to adjust level-of-detail, depth-of-field or game difficulty based on user gaze

Publication

***Koulieris, G.A.**., Drettakis, G., Cunningham, D., Mania, K. (2015, submitted to IEEE VR special issue Transactions on Visualization and Computer Graphics). Gaze Prediction using Machine Learning for Dynamic Stereo Manipulation.*

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- Summary

Thesis Summary

Context-aware Gaze-predictions and Applications

Model Summary

- We tackled **the challenging problem of incorporating High Level hypotheses and task restrictions** in two real-time gaze prediction models
- Each model specializes to a different family of applications depending on readily accessible scene context information or the availability or not of an eye tracker during attention model formation

Applications Summary

- We developed three gaze-aware applications that exploit the prediction accuracy of our models
  - To adjust game level difficulty
  - Optimize GPU performance on mobile devices
  - Reduce eye strain when watching stereoscopic 3D content

Future Work

Context-aware Gaze-predictions and Applications

Dynamic Game Balancing and AI

Dynamically adjust game difficulty and AI at run-time based on gaze

Cinematography effects

Apply post-process cinematography effects based on gaze, e.g. Depth-of-Field, Light Adaptation

In-App Advertising

Employ our models to select the most attended locations in the Field of View for Ad placement

Gaze prediction to improve eye-tracking

Improve the accuracy of mobile, front facing camera eye tracking via gaze prediction

Relevant Publications
Journal & Peer-Reviewed Conference Papers & Posters

Koulieris, G.A., Drettakis, G., Cunningham, D., Mania, K. (2015, submitted to IEEE VR special issue Transactions on Visualization and Computer Graphics). Gaze Prediction using Machine Learning for Dynamic Stereo Manipulation.

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). C-LOD: Context-aware Material Level-of-Detail applied to Mobile Graphics. In Computer Graphics Forum Vol. 33, No. 4, p. 41-49.

Sidorakis, N., **Koulieris, G.A.**, Mania, K. (2015, March). Binocular Eye-Tracking for the Control of a 3D Immersive Multimedia User Interface. IEEE VR conference, 1st Workshop on Everyday Virtual Reality (WEVR), p. 15-18.

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McNamara, A., Mania, K., **Koulieris, G.A.**, Itti, L. (2014, July). Attention-aware rendering, mobile graphics and games. In ACM SIGGRAPH 2014 Courses, p. 85-112.

Koulieris, G.A., Drettakis, G., Cunningham, D., Sidorakis, N., Mania, K. (2014, July). Context-aware material selective rendering for mobile graphics. In ACM SIGGRAPH 2014 Posters, p. 92. **[won 3rd place at the ACM Graduate Student Research Competition]**

Paraskeva, C., **Koulieris, G.A.**, Coxon, M., Mania, K. (2012, December). Gender differences in spatial awareness in immersive virtual environments: a preliminary investigation. In Proceedings of the 11th ACM SIGGRAPH International Conference on Virtual-Reality Continuum and its Applications in Industry, p. 95-98.

Thank you!

Questions?

Acknowledgments

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European Union
European Social Fund

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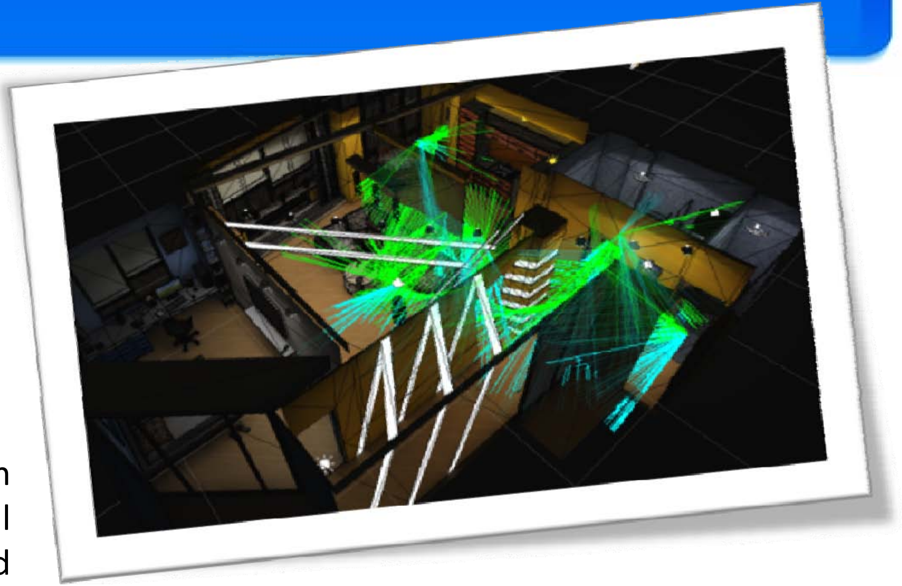
EDUCATION AND LIFELONG LEARNING
investing in knowledge society
MINISTRY OF EDUCATION & RELIGIOUS AFFAIRS, CULTURE & SPORTS
MANAGING AUTHORITY
Co- financed by Greece and the European Union

NSRF 2007-2013
programme for development
EUROPEAN SOCIAL FUND



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