CUTTING-EDGE VR/AR DISPLAY TECHNOLOGIES (GAZE-, ACCOMMODATION-, MOTION-AWARE AND HDR ENABLED

GAZE-AWARE DISPLAYS

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IEEE Virtual Reality 2018

OVERVIEW

- **9:00 – 9:30: Introduction**
- **9:30 – 10:15: Multi-focal displays**
- 10:30 - 11:00: Coffee break
- **11:00 – 11:50: Near-eye varifocal AR**
- 12:00 - 14:00: Lunch
- **14:00 – 14:40: HDR-enabled displays**
- **14:45 – 15:25: Gaze-aware displays**
- 15:30 – 16:00: Coffee break
- **16:00 – 16:50: Motion-aware displays**
- **17:00 – 17:20: Panel**

OVERVIEW

- **GAZE PREDICTION** (CNN/LEARNING, LOW/HIGH, MESH SALIENCY, VR/360)
- **GAZE TRACKING** (FOR VR, SELF-CALIBRATION EYE GAZE TRACKING IN VR)
- **GAZE DIRECTION** (WEB DESIGNS, ATTENTION-BASED COMPOSITION MANGA)
- **FOVEATED RENDERING**
- **STEREO GRADING**
- **3D UIS BASED ON GAZE, GAZE-DRIVEN VIDEO RE-EDITING, FACIAL RE-ENACTMENT IN VR WITH EYE GAZE CONTROL**
- **CONCLUSIONS**

GAZE PREDICTION

Eye tracking, Low-level, Task-based, High-level saliency

GAZE PREDICTION MODELS

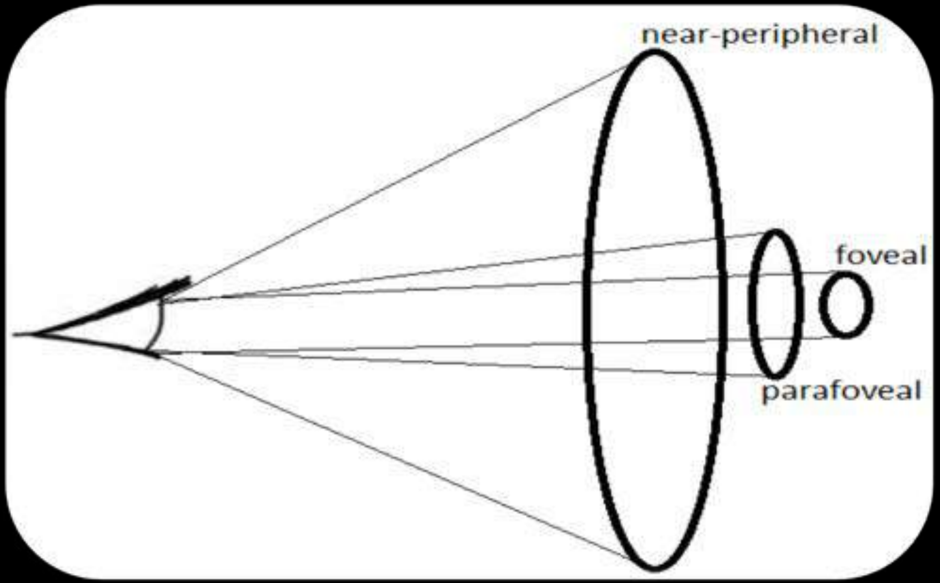
Gaze Prediction

- **Gaze prediction** can **accelerate image synthesis** by reducing computation on non-attended scene regions
- Controlling **the level of detail in geometric models** (zotos et al., 2009)
- Controlling **image resolution in foveated rendering** (Patney et al 2016, guenter et al, 2015)
- Controlling **the state of luminance adaptation in tone mapping** (jacobs et al 2015)
- Gaze Prediction of saccades landing positions **to reduce system latency** (Arabadzhiyska et al 2017)
- Attention models **select the best views to scan** indoor scenes in order to produce 3D models (Xu et al 2016)
- High level saliency models **to optimize an LOD manager** based on predicted gaze on objects on mobile platforms (Koulieris et al. 2014)
- Automated high level **saliency prediction of game balancing** (Koulieris et al. 2014)
- Predicting **tactile mesh saliency** (Lau et al., 2016)

- **Eye tracking-based, low-level, high-level, task-based**

EYE TRACKING BASED MODELS

Gaze Prediction - Eye tracking



- HOWEVER, THERE IS LATENCY AND RARELY AVAILABLE FOR COMMON APPLICATIONS

Gaze-based Level-of-Detail
McConkie and Loschky, 1997

VISUAL PERCEPTION
LEVELS OF ABSTRACTION

Gaze Prediction – Low level Saliency

Active extraction and manipulation of environmental information

- **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

Marr et al., 1982, Shipley et al., 2001

FOCAL ATTENTION

MID- & HIGH-LEVEL FEATURES

Gaze Prediction – Low level Saliency

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?

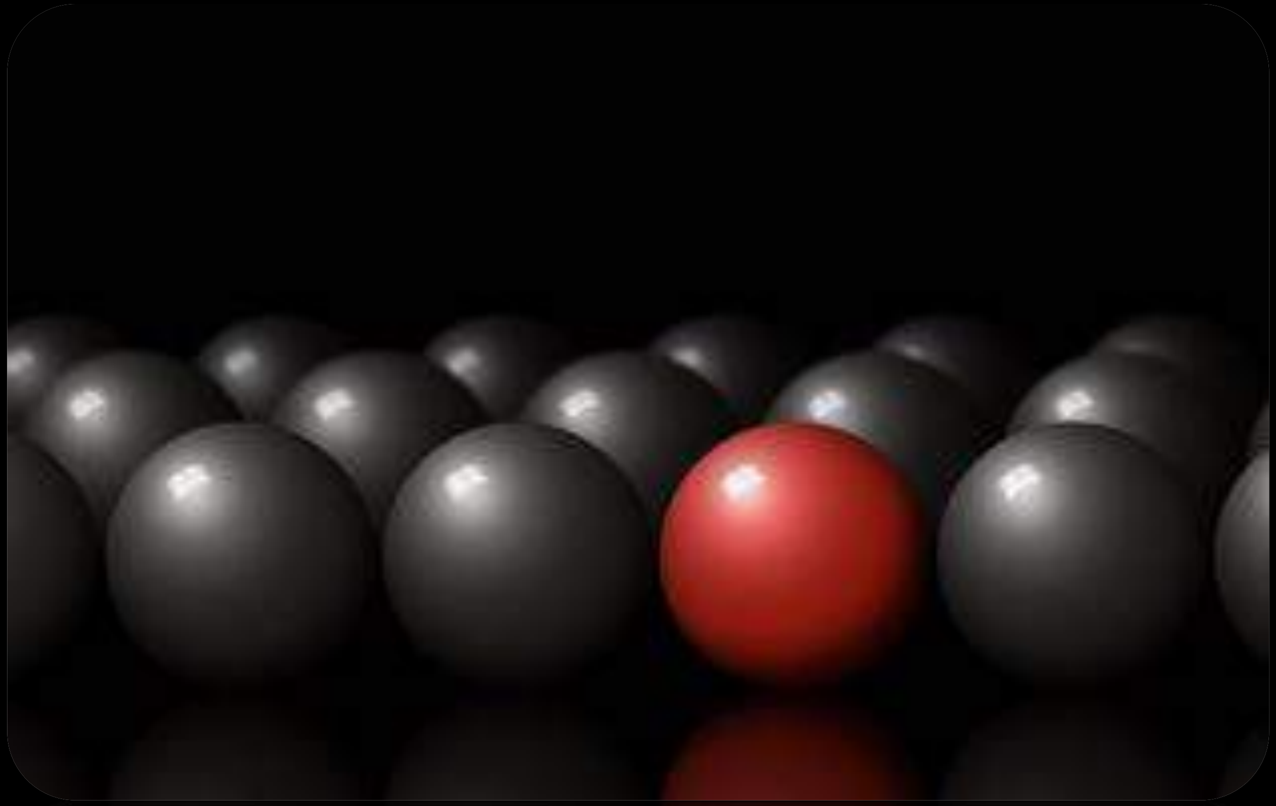
- Influence of low-, mid-, and high-level factors on attention remains unanswered

Theeuwes 2010

ATTENTION PREDICTION

SALIENCY BASED ON LOW-LEVEL IMAGE FEATURES

Gaze Prediction – Low level Saliency



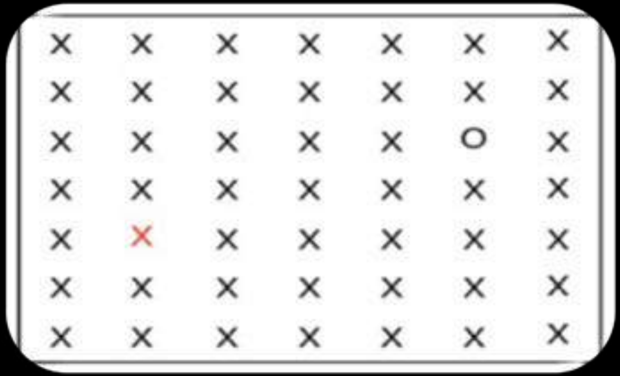
FOCAL ATTENTION MODEL

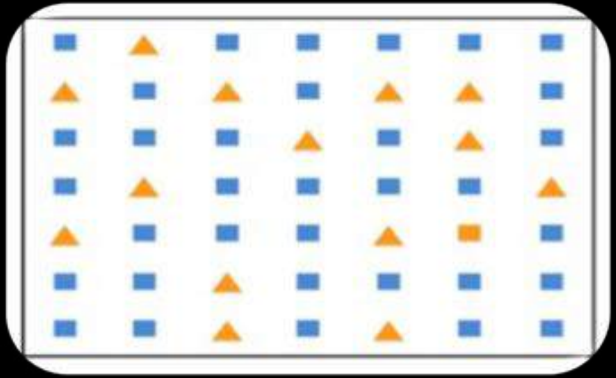
FEATURE INTEGRATION THEORY (FIT): A TWO STAGED-MODEL

Gaze Prediction – Low level Saliency

Stage 1

- LOW-LEVEL FEATURES ARE INITIALLY EXTRACTED EVERYWHERE IN AN IMAGE IN PARALLEL
- FOCAL ATTENTION SELECTS A PRIVILEGED SET OF IMAGE LOCATIONS FOR FURTHER PROCESSING





Stage 2

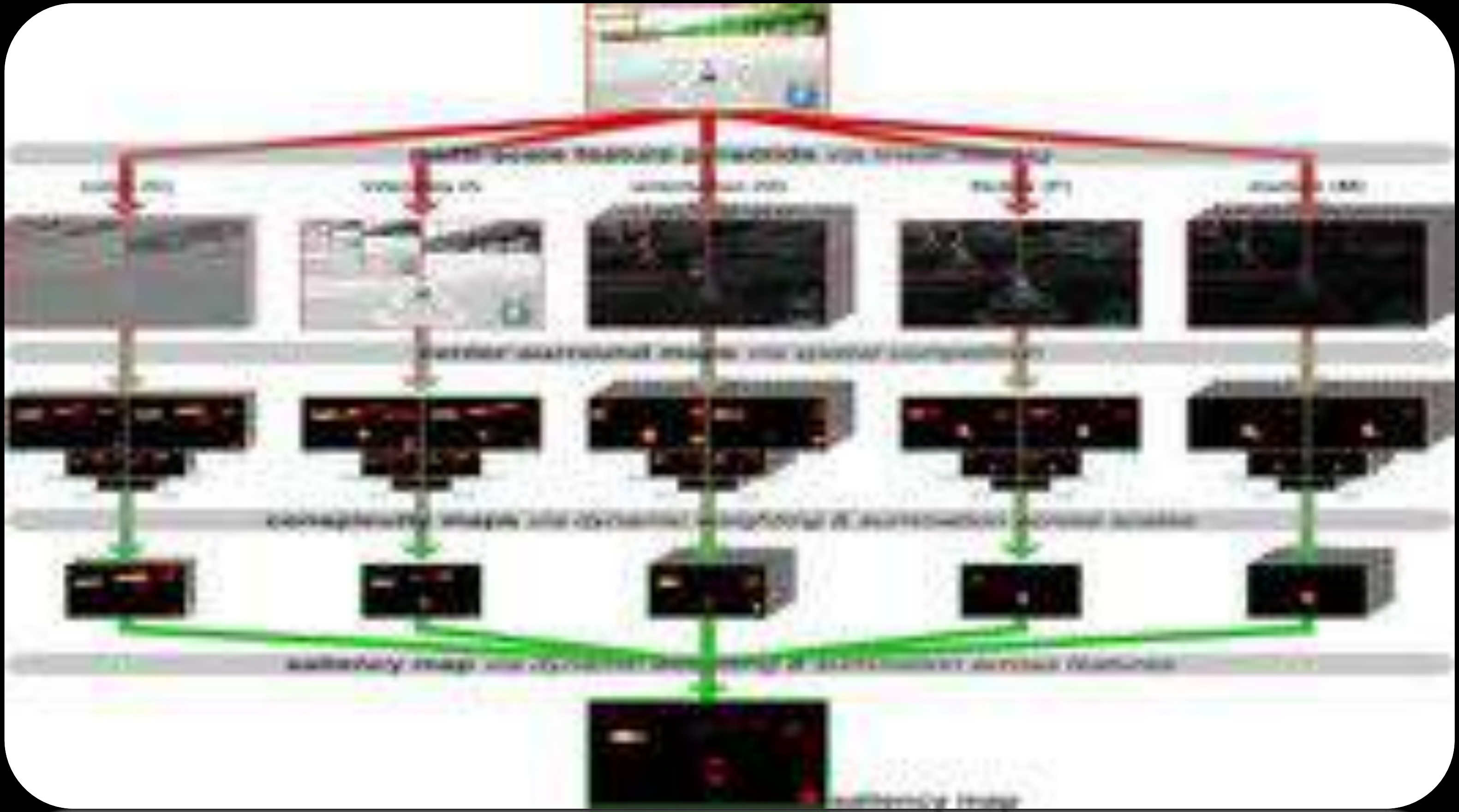
- LOW LEVEL FEATURES AT THE SELECTED LOCATIONS ARE INTEGRATED AND SUBJECTED TO FURTHER PROCESSING IN A SLOW, SERIAL, ONE REGION AT A TIME FASHION

Treisman & Gelade 1980

FEATURE INTEGRATION THEORY

A COMPUTATIONAL MODEL

Gaze Prediction – Low level Saliency



Visual input is first decomposed into a set of topographic feature maps

Itti et al. 1998, Itti & Koch 2000, Yee et al. 2001

PREDICTING ATTENTION

WHY DOES FIT FAIL?

Gaze Prediction – Low level Saliency

FIT fails

- COMPLEX STIMULI SUCH AS SURFACES ARE PROCESSED SIMULTANEOUSLY - NOT SERIALLY
- MULTIPLE SIMULTANEOUS FOCI OF ATTENTION CAN BE ACHIEVED - NOT SUPPORTED BY FIT
- VISUAL ATTENTION DIRECTED TO OBJECTS - NOT ONLY TO LOW LEVEL VISUAL ATTRIBUTES
- HIGH-LEVEL PROPERTIES SUCH AS SCENE SEMANTICS OR TASK AFFECT THE PLANNING AND EXECUTION OF FIXATIONS

Nakayama et al. 1986, O'Craven et al.1999, Awh and Pashler 2000

LOW-LEVEL ATTENTION-AWARE APPLICATIONS

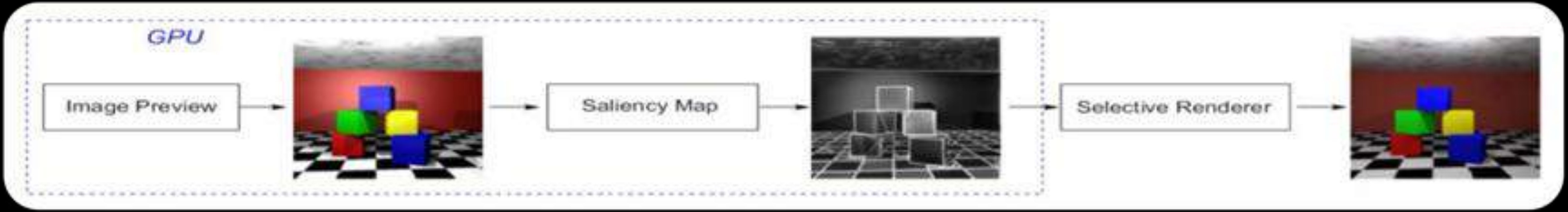
LEVEL-OF-DETAIL

Gaze Prediction – Low level Saliency

FIT-guided selective rendering

- **FIT-BASED SELECTIVE RENDERING, IMPORTANT PARTS RENDERED IN HIGH QUALITY, REMAINING AREAS RENDERED AT LOWER QUALITY**

Suffers from low prediction accuracy when a Task is being conducted and High level semantic context properties drive attention **top-down**; e.g. when searching for an object



Longhurst et al. 2006

SIMULATING GAZE BEHAVIOR

CHARACTERS AND CROWDS

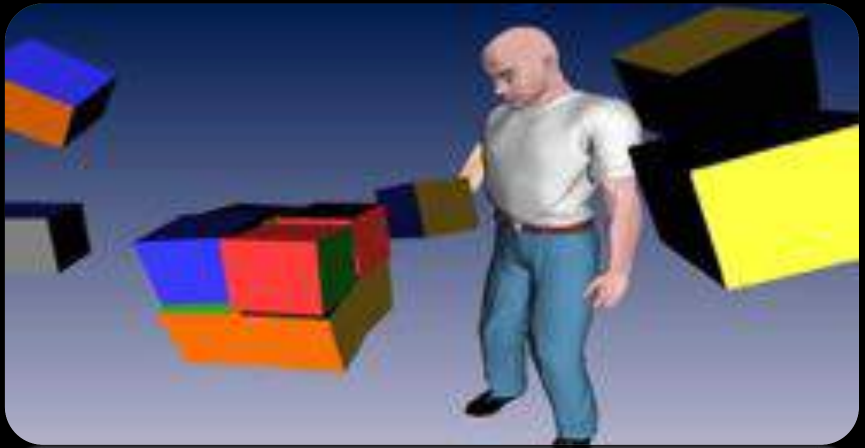
Gaze Prediction – Low level Saliency

Simulating gaze behavior

Saliency models used **to animate gaze behavior of characters**, crowds by extracting scene interest points determining where and when each character should look.

Enforcing in character IK solvers

- LIMITED TO LOW-LEVEL SALIENT OBJECTS
- CHARACTERS AND CROWDS NOT RESPONDING NATURALLY TO TASKS



Oyekoya et al. 2009

Grillon and Thalmann 2009

TASK-RELATED SALIENCY

SALIENCY BASED ON TASK DEMANDS

Gaze Prediction – Task based Saliency

Modeling goal-oriented attention

Counting teapots

- **TASK RELEVANT OBJECTS ATTRACT ATTENTION**
- **TASK IMPORTANCE MAPS** MAY BE USED TO ACCELERATE RENDERING BY REDUCING QUALITY IN REGIONS THAT ARE UNRELATED TO A GIVEN TASK
- **SUBJECTS WILL CONSISTENTLY FAIL TO NOTICE DEGRADATIONS** OF QUALITY UNRELATED TO TASK, EVEN WHEN THESE DETAILS FALL UNDER THE VIEWERS' GAZE

Cater et al. 2003

Task is predetermined
Task has to be pre-determined thus these approaches are very limited

TASK-RELATED SALIENCY

COMBINING TASK-BASED METHODS AND LOW LEVEL FEATURES

Gaze Prediction – Task based Saliency

Low level & task-based and goal-directed methods

- **SALIENCY MODELS AND TASK RELATED DATA LINEARLY COMBINED** TO TRACK VISUALLY ATTENDED OBJECTS IN A VE IDENTIFIYING THE MOST PLAUSIBLY ATTENDED OBJECTS AMONG CANDIDATES IN THE OBJECT SALIENCY MAP
- TASK RELEVANT GAZE BEHAVIOR ESTIMATED BY COMBINING BOTTOM-UP AND TOP-DOWN COMPONENTS TO COMPUTE USER GAZE POINT
- **DEMONSTRATING HOW THE VISUAL ATTENTION TRACKING FRAMEWORK CAN BE APPLIED TO MANAGING THE LEVEL OF DETAILS IN VES**

Lee et al. 2009, Hillaire et al. 2010

Navigation in VR

MACHINE LEARNING APPROACHES

IMPLICIT MODELING OF HIGH LEVEL EFFECTS

Gaze Prediction – High Level Saliency

Gaze Prediction Heuristics for 3D Action Games - Machine Learning on eye tracking data

- **MACHINE LEARNING TECHNIQUES APPLIED TO EYE TRACKING** DATA TO TRAIN A SALIENCY DETECTION MODEL FOR PRE-DEFINED SETS OF STATIC PHOTOGRAPHS (JUDD ET AL. 2009)
- IMPORTANCE MAP SCORING GAZE AMOUNT ON OBJECTS, THEN AS HEURISTIC TO PREDICT GAZE (BERNHARD 2010)
- DERIVE GAZE PREDICTION HEURISTICS FROM EYE-TRACKING DATA FOR 3D ACTION GAMES

Visually highlighting important objects (b) not just salient pixels (c)

(a) (b) (c)

Judd et al. 2009, Bernhard et al. 2010

HIGH LEVEL SALIENCY

MAPPING VISUAL REPRESENTATIONS TO MEANING AND SEMANTICS

Gaze Prediction – High Level Saliency

- PRE-EXISTING KNOWLEDGE ABOUT A CONTEXT, E.G. "BEDROOM"
- KNOWLEDGE FROM ATTENTIONAL PROCESSING
- **CONSISTENT OBJECTS** EXPECTED TO BE FOUND IN A SCENE ARE RENDERED IN LOWER QUALITY BUT RECOGNIZABLE -- **INCONSISTENT ITEMS** WHICH ARE SALIENT REQUIRE HIGH QUALITY
- DEVISING A GENERIC SET OF RULES APPLICABLE TO ANY CONTEXT IS CHALLENGING
- A PREDICTOR THAT CAN BE ADAPTED TO DIFFERENT TASKS

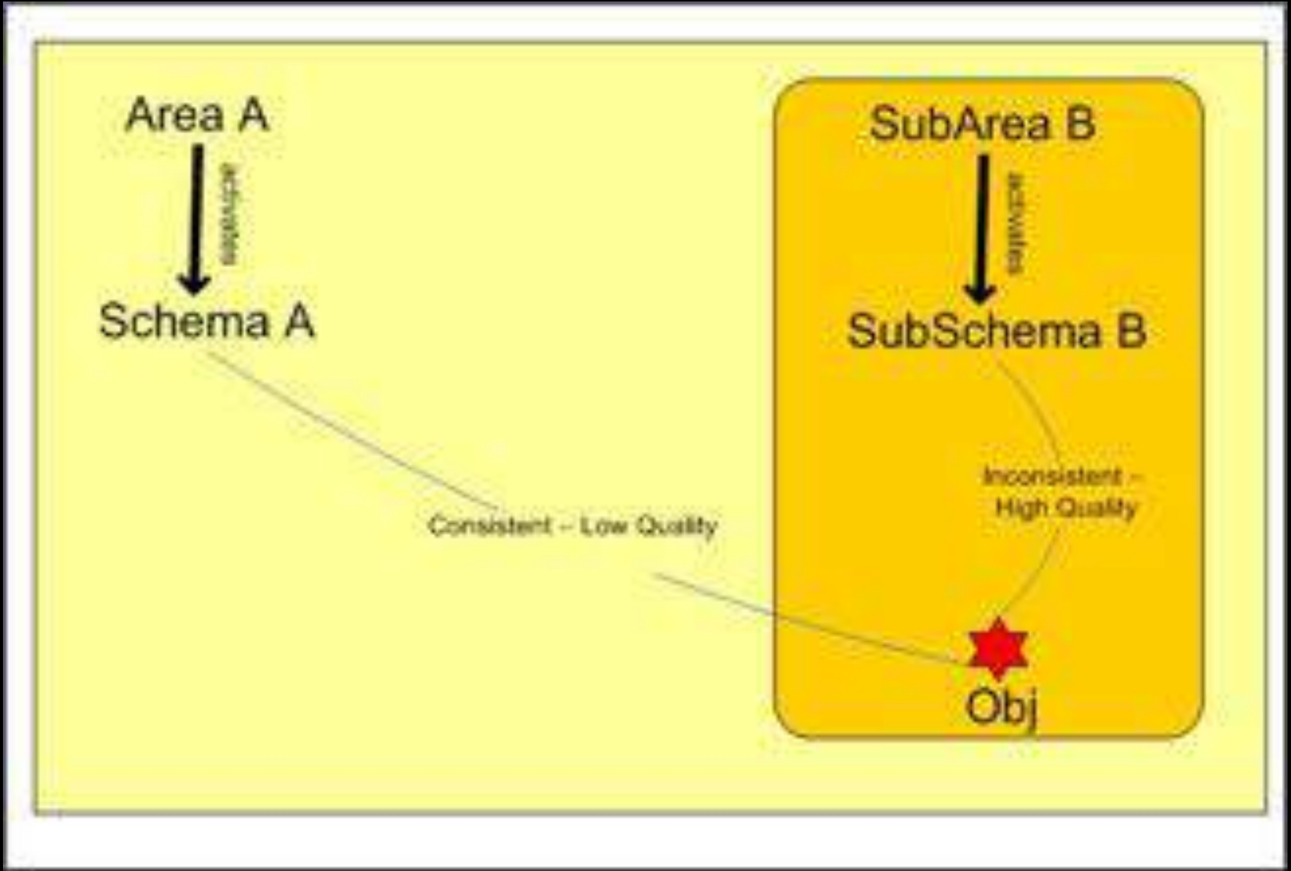
Research in VEs confirmed that attention is influenced by semantic object context

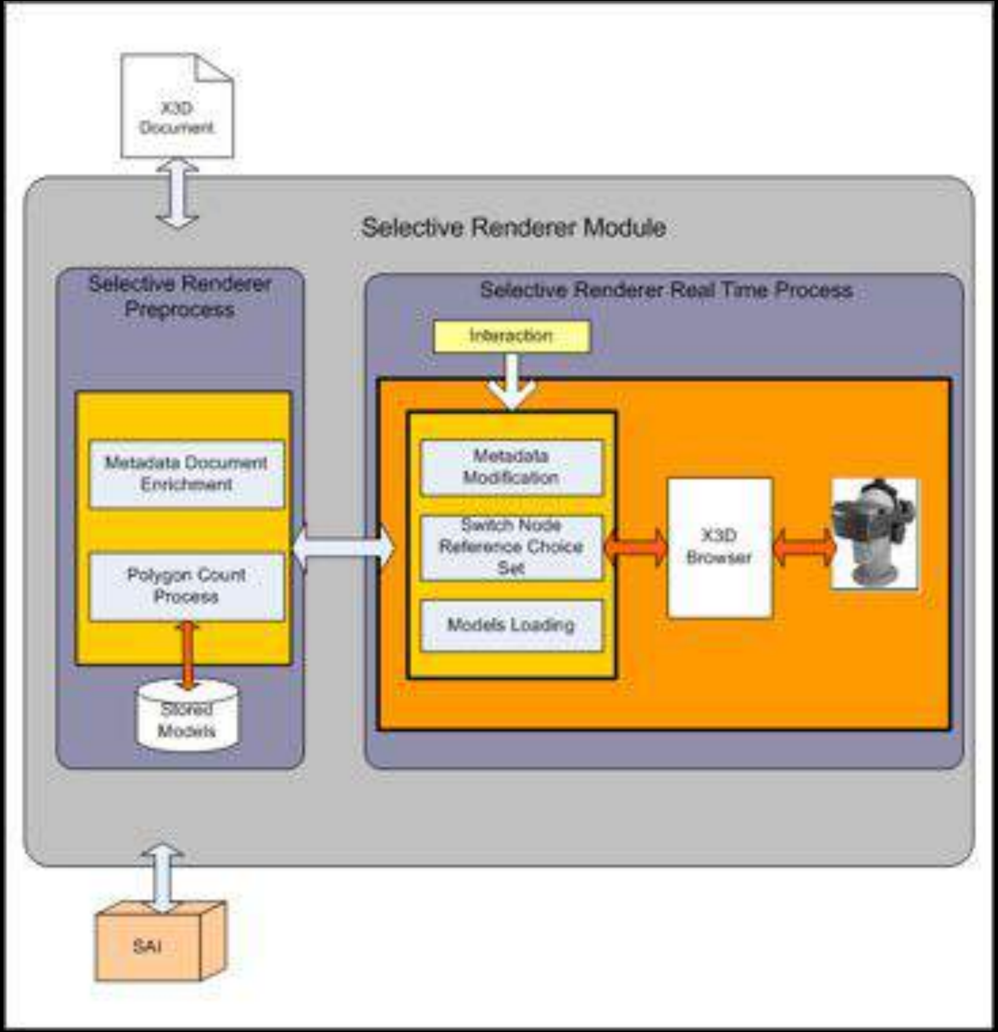
Mania et al. 2005; Mourkoussis et al. 2010; Zotos et al. 2009

HIGH LEVEL SALIENCY

MAPPING VISUAL REPRESENTATIONS TO MEANING AND SEMANTICS

Gaze Prediction – High Level Saliency





Mania et al. 2005; Mourkoussis et al. 2010; Zotos et al. 2009

HIGH LEVEL SALIENCY

MAPPING VISUAL REPRESENTATIONS TO MEANING AND SEMANTICS

Gaze Prediction – High Level Saliency

A High Level Saliency Predictor

- **The 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

Koulieris et al 2014

Koulieris et al 2014

HIGH LEVEL SALIENCY

HYPOTHESES

Gaze Prediction – High Level Saliency

1. Scene Schemata – Out-of-context objects are salient

Brewer & Treyens, 1981

2. Physical Singletoness- Physically isolated objects pop out

Theeuwes & Godijn, 2002

3. Canonical Form of objects - Objects in Non-Canonical Form attract attention

Becker et al., 2007

HIGH LEVEL SALIENCY

HYPOTHESES

Gaze Prediction – High Level Saliency

4. Contextual Singletoness - Contextually isolated objects are salient

5. Temporal object coherence

RECURRING FIXATIONS ARE GENERATED FOR INCONSISTENT OBJECTS AND OBJECTS IN A NON-CANONICAL FORM

6. Feature uniqueness property

A SINGLE SALIENT FEATURE POPS-OUT MORE INTENSELY THAN WHEN SEVERAL SALIENT FEATURES EXIST

Becker et al.,2007, Henderson et al., 1999
Frintrop et al., 2010

A COMPUTATIONAL MODEL OF HIGH LEVEL SALIENCY MODELING

ROOTS: THE DIFFERENTIAL WEIGHTING MODEL (DWM) *ECKSTEIN, 1998*

Gaze Prediction – High Level Saliency

A single staged model

- ATTENTIONAL PROCESSING VIA GAUSSIAN COMBINATION RULES. EVERY OBJECT IN THE SCENE HAS A SET OF BAYESIAN PRIORS ON THE AREAS THAT THE OBJECT IS EXPECTED TO BE ATTENDED
- THE CHIMNEY HIGH PROBABILITY OF ATTENDANCE ON THE TOP ROOF, LOW IN OTHER AREAS
- IN PERCEPTUAL EXPERIMENTS IT IS VERIFIED THAT HIGH LEVEL SALIENCY GUIDES ATTENTION AND WEIGHTS OF EACH HYPOTHESIS ARE DERIVED SO THAT THE MODEL IS CALIBRATED
- THE POSTERIOR PROBABILITY IS CALCULATED THAT THE VIEWER WILL FIXATE ON AN OBJECT INDEPENDENT OF TASK

Koulieris et al, 2014a, 2014b

PERCEPTUAL STUDIES

Gaze Prediction – High Level Saliency

Stimuli

- **EXAMINE THE EFFECTS OF SIX HYPOTHESES ON VISUAL ATTENTION -- OBTAIN CONTRIBUTION WEIGHTS OF EACH FACTOR FOR THE MODEL**
- NAVIGATE AROUND TO FIND AND COLLECT 3 OBJECTS. TASK ACCURACY, COMPLETION TIME, AND EYE-TRACKING DATA WERE RECORDED ALTERING OBJECT PLACEMENT BASED ON CONDITION
- THE PREDICTED COMPLETION TIME IS DIVIDED BY THE ACTUAL COMPLETION TIME IN EACH CONDITION
- **THE RELATIVE EFFECT OF ALTERING ONE FACTOR IS CALCULATED**
- EYE-TRACKING REGIONS-OF-INTEREST (ROIS) SHOWED THAT ATTENTION IS INDEED ATTRACTED BOTH TO CONTEXTUALLY SINGLETON OBJECTS AND TO OBJECTS IN A NON-CANONICAL FORM

Koulieris et al, 2014a, 2014b

HSLM - THE HIGH LEVEL SALIENCY MODELER

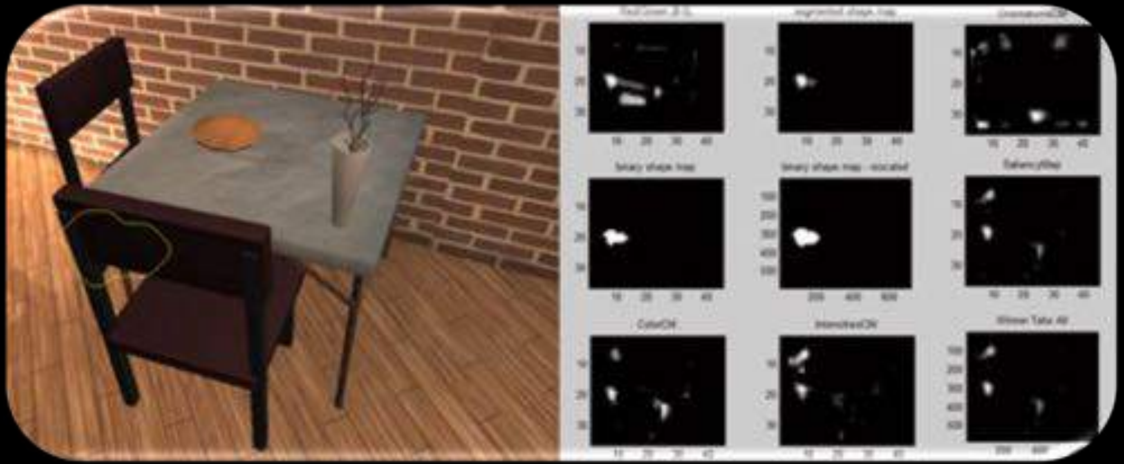
GPU BASED IMPLEMENTATION

Gaze Prediction – High Level Saliency

Implementation

- Estimates in real time a posterior probability term of attendance in a shader, based on viewpoint, i.e. an object may or may not appear as singleton depending on the viewpoint
- Identifies objects expected to attract attention

High Level Saliency



Low Level Saliency

Koulieris et al, 2014a, 2014b

EVALUATION OF GAME LEVEL EDITING

GAME BALANCING - EYE-TRACKING DATA HEAT MAPS

Gaze Prediction – Application of HL-Saliency

Game Level Editing

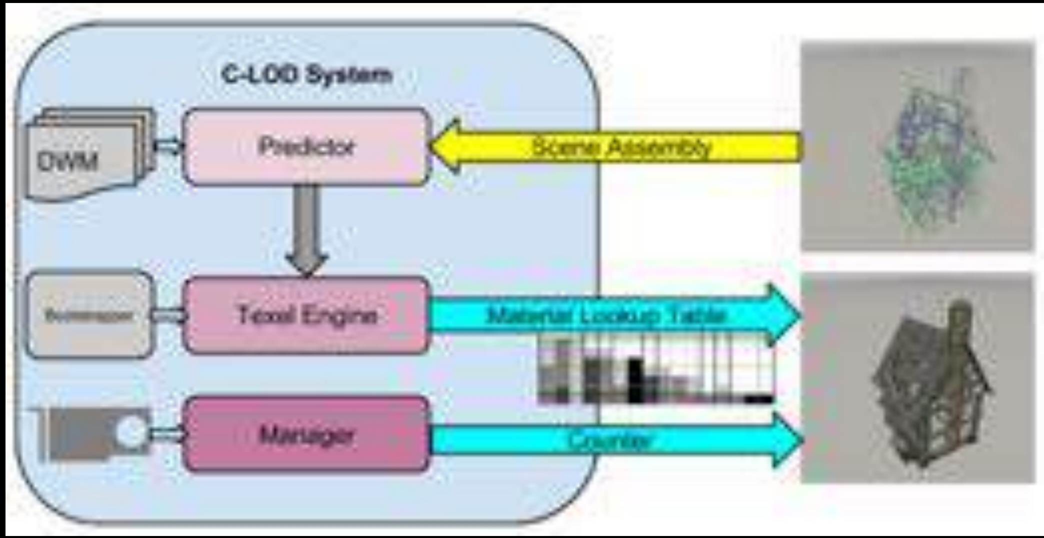
- **LOOKING FOR AN OBJECT IS A COMMON TASK IN (ACTION-)ADVENTURE VIDEO GAMES**
- PLOT-CRITICAL OBJECTS ARE PLACED IN SELECTED LOCATIONS TO EASE OR BURDEN THE PLAYER
- **MAINTAIN CHALLENGE AID GAME LEVEL DESIGNER TO IDENTIFY OBJECT SALIENCY DEPENDING ON LOCATION**

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

C-LOD CONTEXT AWARE MATERIAL LOD

SCHEMATIC

Gaze Prediction – High Level Saliency



A generic material LOD manager based on attention for Unity 3D game engine

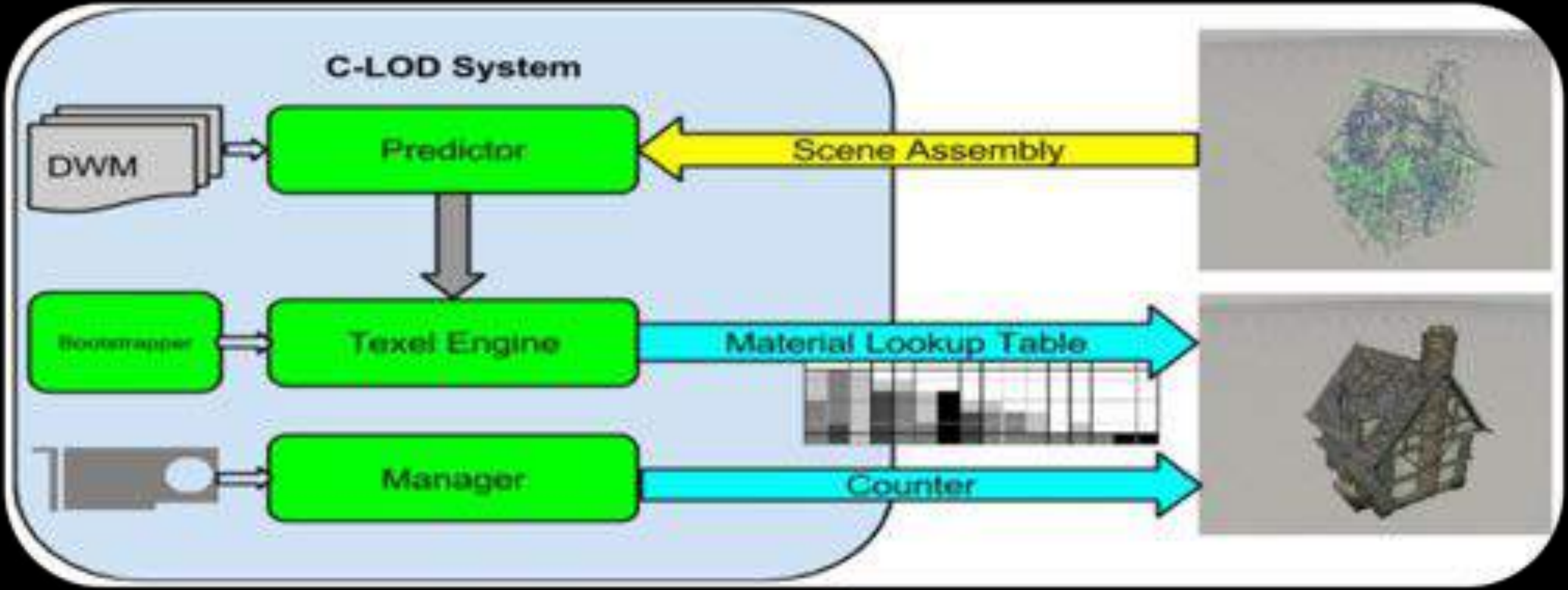
C-LOD is a reactive fixed frame rate scheduler that constantly examines frame rate and attention deployment predictions. When frame rate drops below 30 frames per second on mobile devices, C-LOD automatically **lowers the rendering quality of objects predicted not to be attended** until performance is restored.

Koulieris et al, 2014a, 2014b

C-LOD FOR UNITY 3DTM

C-LOD COMPONENTS

Gaze Prediction – Applications of HL-Saliency



<u>The Texel Engine</u> C-LOD's Texel Engine constantly **monitors object predictions derived from the attention model. A special 2D texture is updated that works as a material quality lookup table**

<u>The Bootstrapper</u> **The interaction between the graphics processor, CPU and memory of a mobile device. The materials managed are initially rendered at their lowest quality.** Then, in rapid succession, the quality level of each object's material is increased while frame rate is monitored.

<u>The Manager</u> **A Finite State Machine (FSM) monitors frame rate during execution. When frame rate drops and motion is detected, a counter is increased.** This counter is communicated to all managed materials. Frame rate is constantly re-evaluated and the counter is increased/ decreased to maintain the best LOD for the current conditions

C-LOD: CONTEXT AWARE MATERIAL LOD FOR MOBILE

ATTENTION-AWARE LOD

Gaze Prediction – HL Gaze Prediction

Level-of-Detail (LOD)

- HIGHER VISUAL FIDELITY FOR AREAS EXPECTED TO ATTRACT ATTENTION
- VISUAL FIDELITY DECREASED FOR NOT ATTENDED SCENE AREAS

Level-of-Detail on Mobile Devices

- INTEREST RECENTLY RENEWED DUE TO EXPLOSIVE GROWTH OF THE MOBILE MARKET
- PROHIBITIVE HARDWARE RESTRICTIONS OF MOBILES FOR COMPLEX EFFECTS

Attention Modeling

CONTEXT NOT TAKEN INTO ACCOUNT BY EXISTING LOD MANAGERS

Koulieris et al. 2014

LOD FOR MOBILE GRAPHICS

C-LOD FOR UNITY 3DTM

Gaze Prediction – Applications of HL-Saliency

Introduction

- REACTIVE FIXED FRAME RATE SCHEDULER BASED ON ATTENTION
- C-LOD LOWERS THE RENDERING QUALITY OF OBJECTS PREDICTED NOT TO BE ATTENDED
- THE HIGHEST QUALITY IS MAINTAINED FOR ALL ATTENDED OBJECTS

THREE COMPLEX EFFECTS USUALLY OMITTED IN MOBILE DEVICES AS THEY REQUIRE MANY TEXTURE FETCHES WERE SELECTED

Subsurface scattering

Refraction

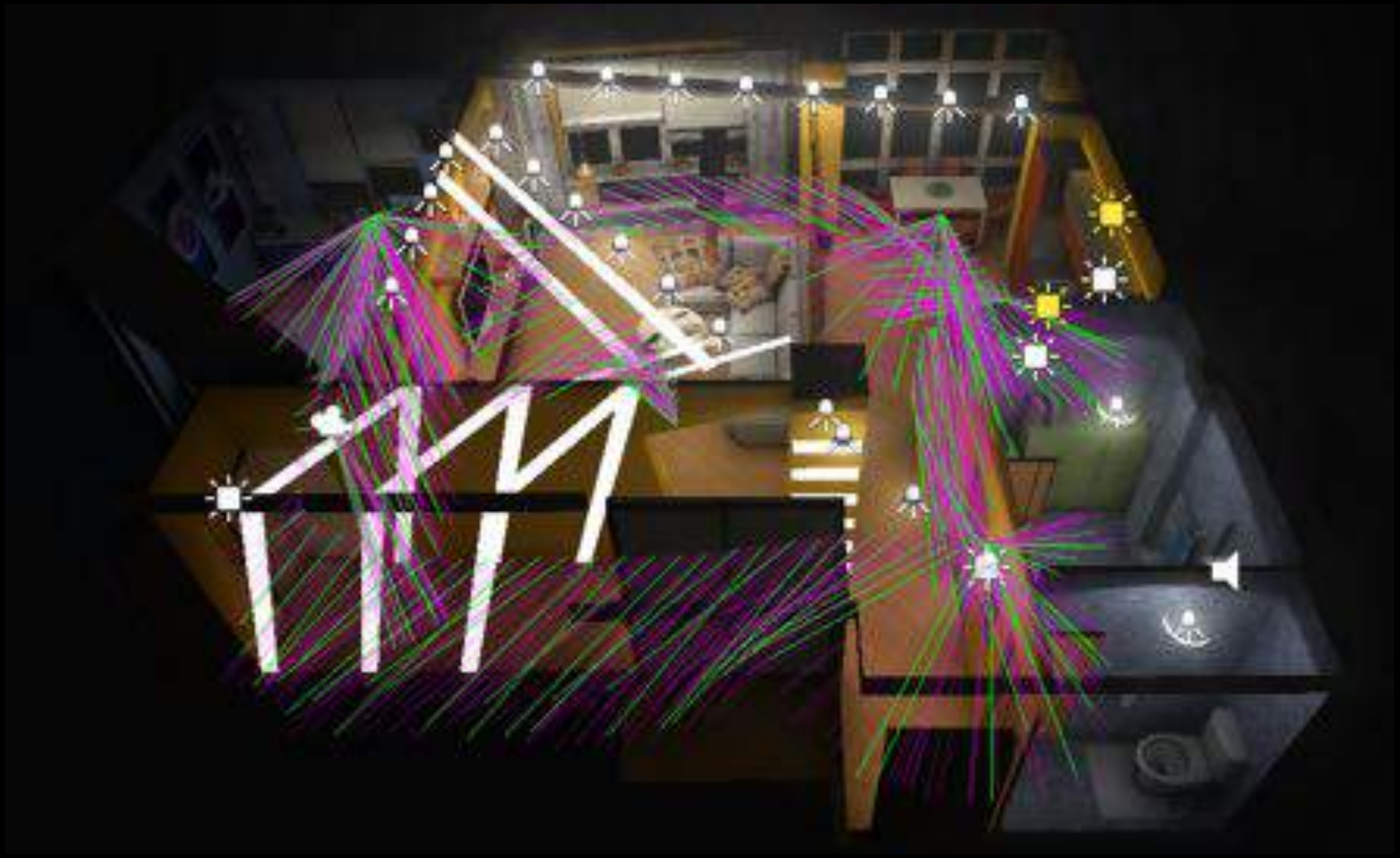
Bump Mapping

Koulieris et al. 2014

LOD FOR MOBILE GRAPHICS

C-LOD FOR UNITY 3D™

Gaze Prediction – Applications of HL-Saliency

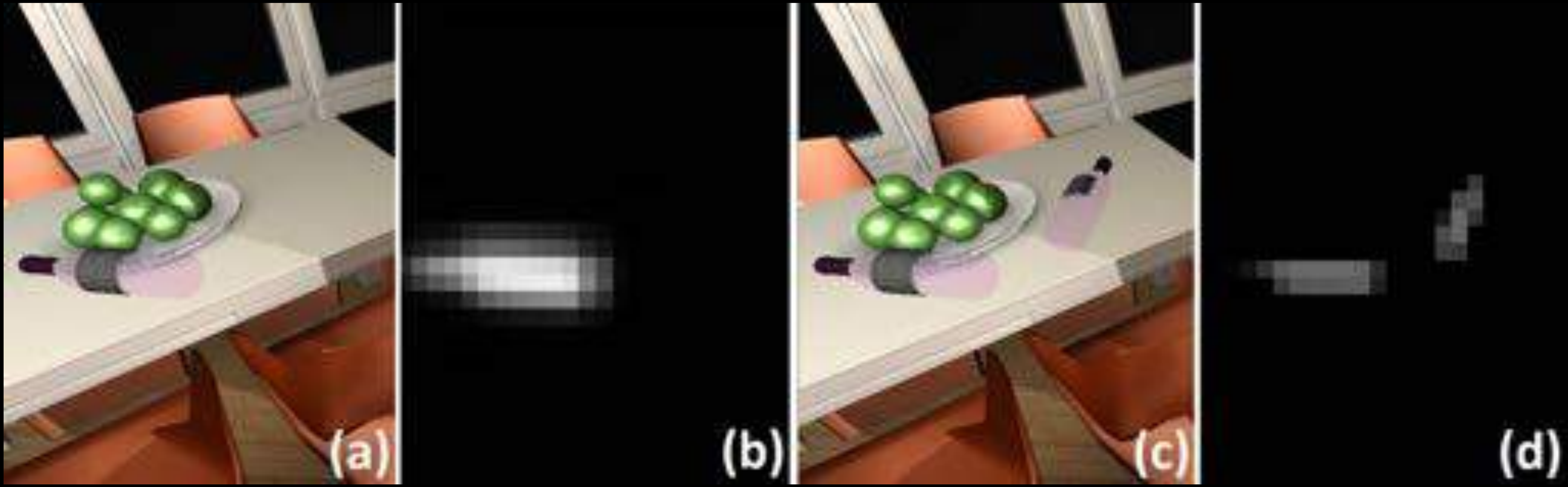


Koulieris et al. 2014

LOD FOR MOBILE GRAPHICS

C-LOD FOR UNITY 3DTM

Gaze Prediction – Applications of HL-Saliency



EVALUATION OF C-LOD

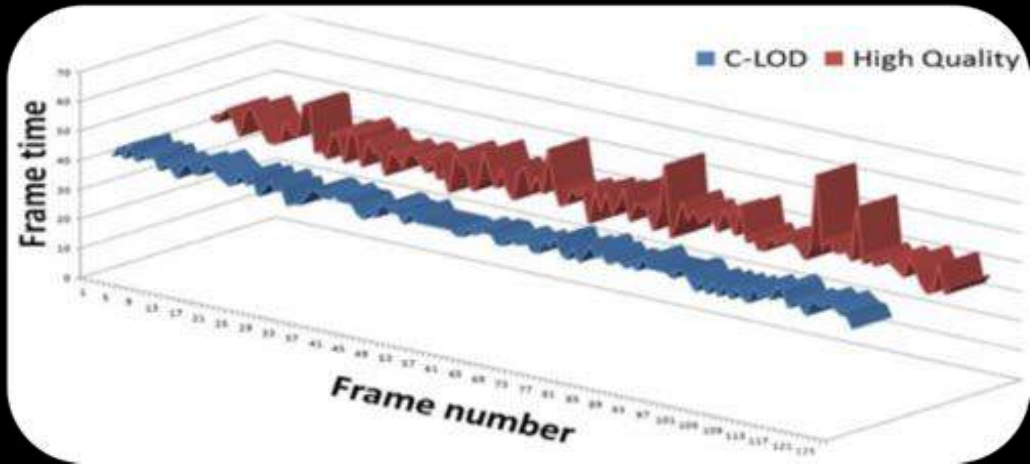
MODEL EFFICIENCY

Gaze Prediction – Application of HL-Saliency

C-LOD optimizes rendering

- **C-LOD: CONSISTENTLY STABLER FRAME RATE THAN HQ, STABILIZES FRAME RATE WITHOUT SACRIFICING**
- **EVALUATION BOTH BY GPU PERFORMANCE, BATTERY PERFORMANCE AND EYE TRACKING**

- C-LOD ESTIMATIONS RUN FOR 4MS ON AVERAGE PER FRAME
- **THE ADDITION OF THE C-LOD CHANGES DID NOT ALTER GAZE PERFORMANCE,** AND THUS WERE MOST LIKELY NOT PERCEIVED BY THE PARTICIPANTS
- PERCEIVED QUALITY AND BOOSTS BATTERY RUN TIME BY 6.5%



Koulieris et al. 2014

SUMMARY

EVALUATION AND CONCLUSIONS

Gaze Prediction – Summary

High Level Saliency can be modeled
Objects identified as non-salient in terms of low level features

- 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
    - **LIMITATION: SEMANTIC TAGGING INFORMATION FOR EACH 3D-MODEL IS REQUIRED FOR THE MODEL TO WORK**

HOW DO PEOPLE EXPLORE VIRTUAL ENVIRONMENTS?

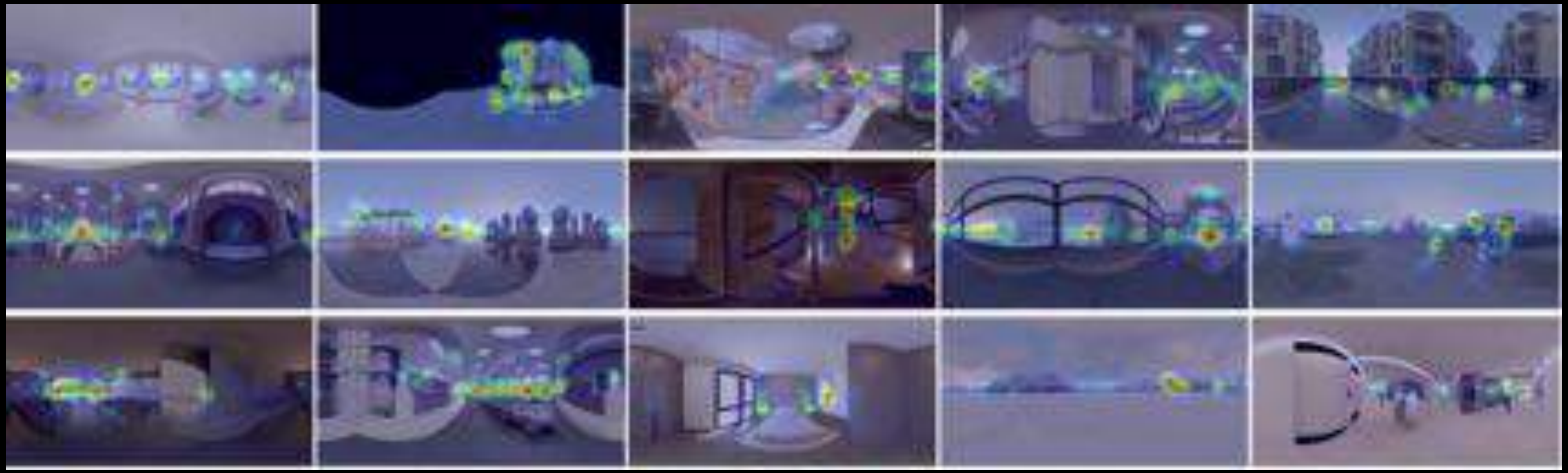
SITZMAN ET AL 2018

Gaze Prediction – VR PANORAMAS

CAPTURE AND ANALYSIS OF GAZE AND HEAD ORIENTATION DATA OF 169 USERS EXPLORING STEREOSCOPIC, **STATIC OMNI-DIRECTIONAL PANORAMAS**, FOR A TOTAL OF 1980 HEAD/GAZE TRAJECTORIES IN VR AND DESKTOP

- GAZE STATISTICS AND SALIENCY IN VR **IN GOOD AGREEMENT** WITH CONVENTIONAL DISPLAYS
- **HEAD ORIENTATION RECORDED** BY INERTIAL SENSORS MAY BE **SUFFICIENT TO PREDICT SALIENCY** WITH REASONABLE ACCURACY WITHOUT THE NEED FOR COSTLY EYE TRACKERS
- **THE FEWER SALIENT REGIONS, THE FASTER USER ATTENTION** GETS DIRECTED TOWARDS ANY OF THEM AND THE MORE CONCENTRATED THEIR ATTENTION IS

22 panoramas recorded scanpaths then compared with saliency



360 mapping to 2D patches for saliency models

HOW DO PEOPLE EXPLORE VIRTUAL ENVIRONMENTS?

SITZMAN ET AL 2018

Gaze Prediction – VR PANORAMAS

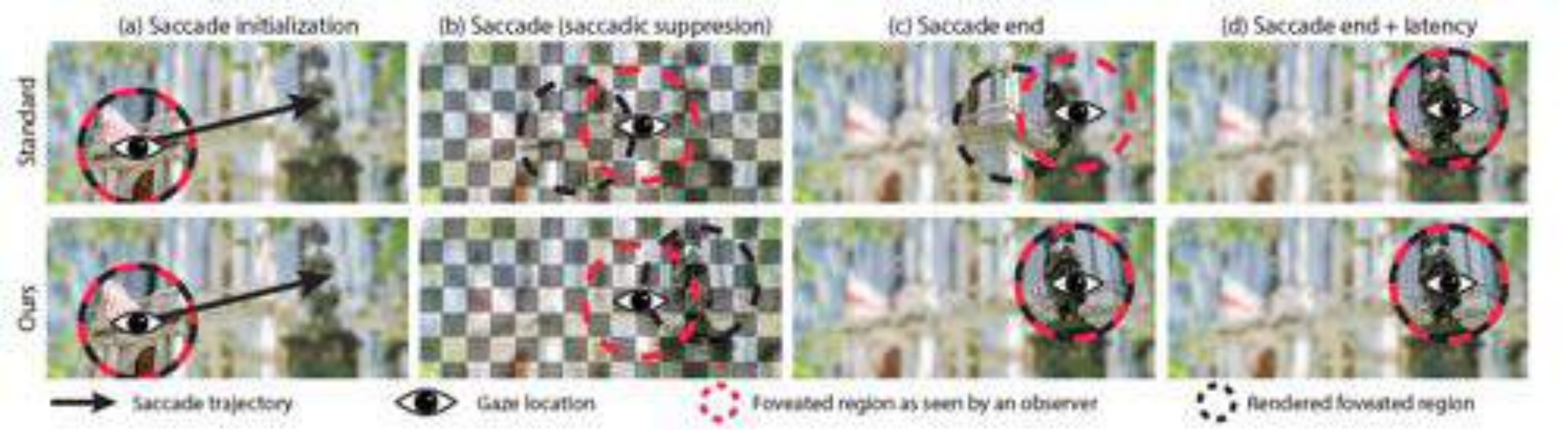
- APPLICATIONS INCLUDE **AUTOMATIC THUMBNAILING, COMPRESSION IN NON-SALIENT AREAS, AUTOMATIC ALLIGNMENT OF CUTS IN VR VIDEO**
- WE CAN ACCURATELY PREDICT TIME-DEPENDENT VIEWING BEHAVIOR ONLY WITHIN THE FIRST FEW SECONDS BUT NOT FOR LONGER PERIODS OF TIME DUE TO THE HIGH INTERUSER VARIANCE

Automatic alignment of cuts in VR video

SACCADE LANDING POSITION FOR GAZE-CONTINGENT RENDERING

Gaze Prediction during saccadic suppression

- **GAZE CONTINGENT RENDERING** IS HAMPERED BY MISMATCH BETWEEN IMAGE QUALITY AND GAZE LOCATION. APPARENT DURING **FAST SACCADIC MOVEMENTS** WHEN THE **INFORMATION ABOUT GAZE LOCATION IS SIGNIFICANTLY DELAYED**, AND THE QUALITY MISMATCH CAN BE NOTICED
- INSTEAD OF RENDERING TO THE CURRENT GAZE POSITION, **THE TECHNIQUE PREDICTS WHERE THE SACCADE IS LIKELY TO END** PROVIDING AN IMAGE FOR THE NEW FIXATION LOCATION AS SOON AS THE PREDICTION IS AVAILABLE **BEFORE** THE FIXATION. THE IMAGE UPDATE IS DONE DURING SACCADIC SUPPRESSION



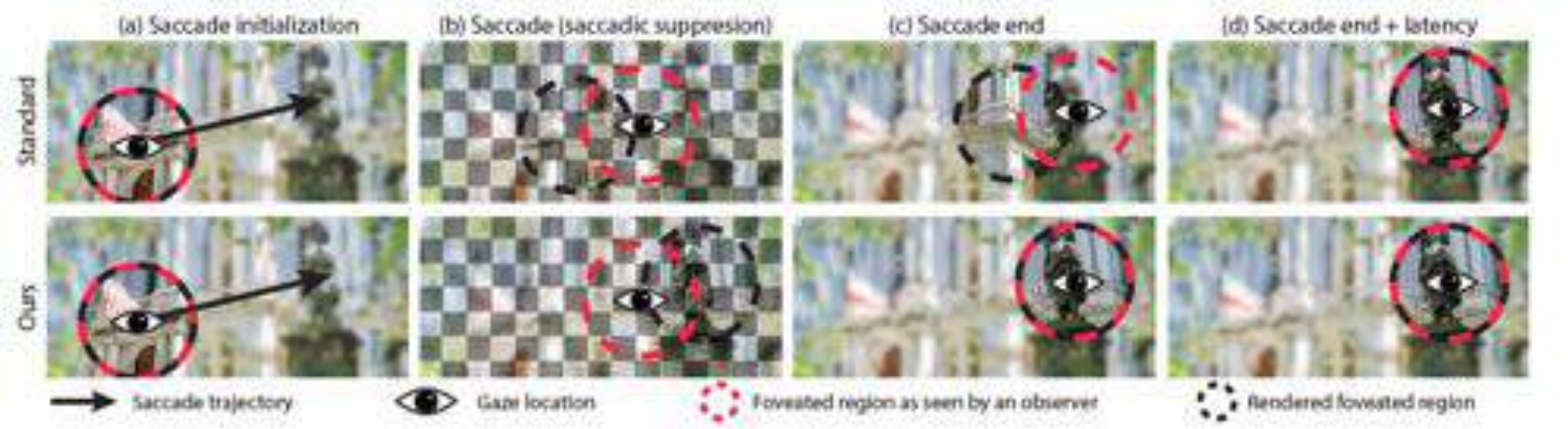
Arabadzhiyska et al. 2017

(b) top -- latency of rendering after saccade
(b) bottom -- rendering on location of predicted saccade, actual following

SACCADE LANDING POSITION FOR GAZE-CONTIGENT RENDERING

Gaze Prediction during saccadic suppression

- COLLECTING SACCADES SAMPLES. A **COMPUTATIONAL MODEL BASED ON BALLISTIC TRAJECTORIES CAPTURES THEIR CHARACTERISTICS** AND USES EYE-TRACKER SAMPLES PREDICTING THEIR LANDING POSITIONS
- **VELOCITY METHOD TO DETECT END/START OF SACCADE WHEN VELOCITY DROPS BELOW A THRESHOLD IS THE END POINT**, PREDICTION RETURNING A VALUE FOR SACCADE AMPLITUDE.
- VR PROBLEMS, MOVEMENT OF HEADSET, LOSS OF GAZE DIRECTION, QUALITY OF THE SCREEN



Arabadzhiyska et al., 2017

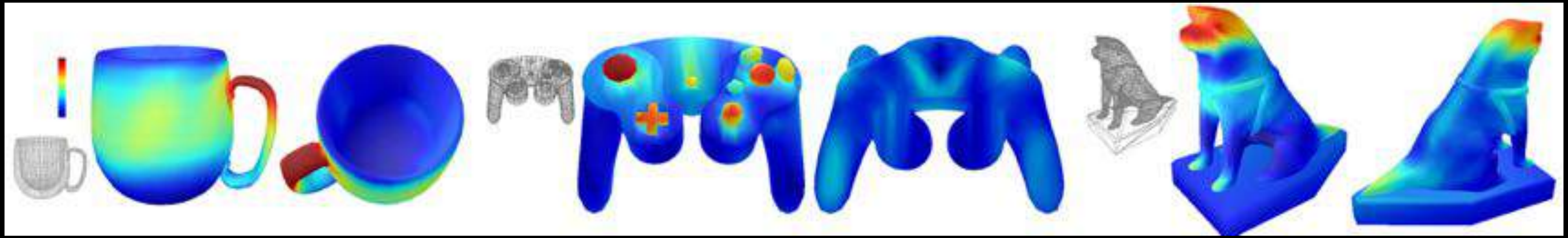
Validation: reducing delay in gaze-contingent rendering user experience

TACTILE MESH SALIENCY

LAU ET AL 2016

Gaze Prediction – Tactile

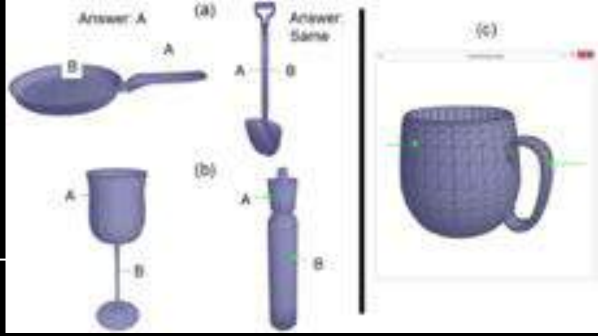
- **TACTILE SALIENCY** -- SALIENT POINTS ON A 3D MESH THAT A HUMAN LIKELY TO **GRASP**, **PRESS** OR **TOUCH**
- TAKING AS **INPUT A 3D MESH -- COMPUTING THE RELATIVE TACTILE SALIENCY** OF EVERY MESH VERTEX
- **COLLECTING CROWDSOURCED DATA OF RELATIVE RANKINGS**
- USERS RANKING WHETHER **ONE POINT IS MORE TACTILE SALIENT THAN OTHER** ON PAIRS OF VERTICES
- COMBINING **DEEP LEARNING AND LEARNING-TO-RANK** TO COMPUTE A TACTILE SALIENCY MEASURE.



Grasp
Press
Touch
Saliency map

TACTILE MESH SALIENCY

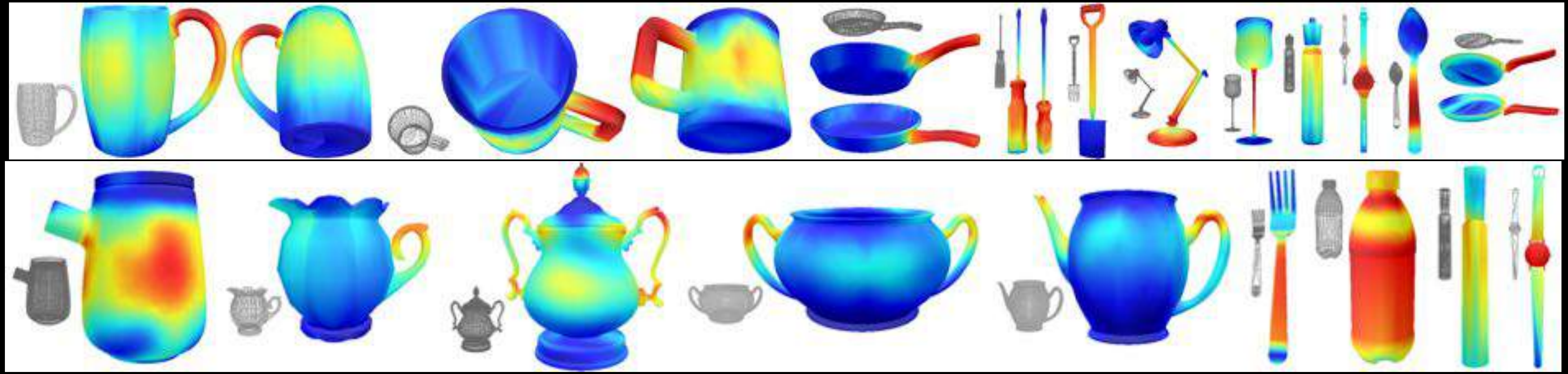
LAU ET AL 2016



Gaze Prediction - Tactile

- REPRESENTING A 3D SHAPE WITH **MULTIPLE DEPTH IMAGES** TAKEN FROM DIFFERENT VIEWPOINTS
- PATCHES ARE TAKEN FROM THE DEPTH IMAGES AND LEARN **A DEEP NEURAL NETWORK THAT MAPS A PATCH TO A SALIENCY VALUE FOR THE PATCH CENTER**
- THE SAME DEEP NEURAL NETWORK CAN BE USED ACROSS DIFFERENT DEPTH IMAGES AND 3D SHAPES. **DIFFERENT NETWORKS FOR EACH TACTILE MODALITY.** AFTER THE LEARNING PROCESS, COMPUTING A TACTILE SALIENCY VALUE FOR EVERY NEW MESH VERTEX

Grasp saliency map, top training data, bottom output



TACTILE MESH SALIENCY -- APPLICATIONS

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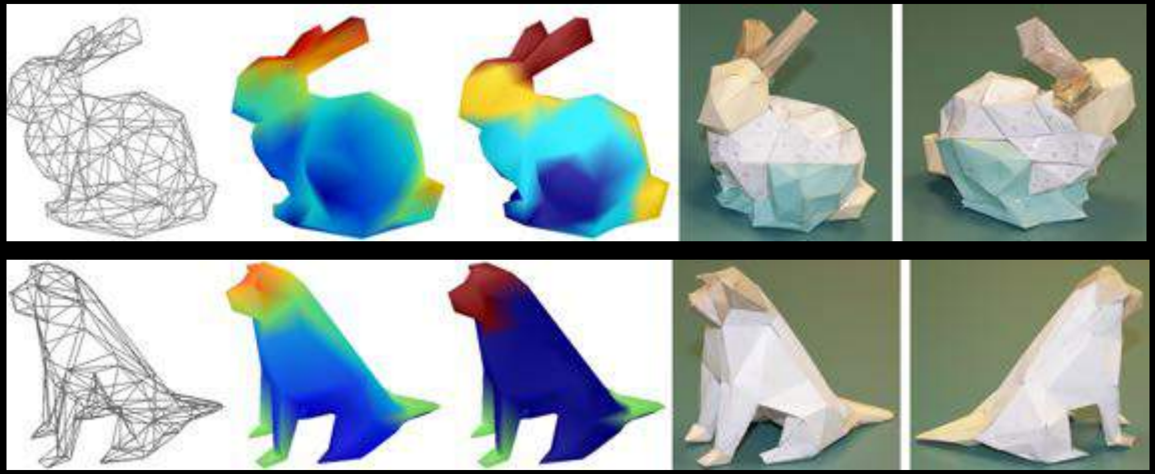
Gaze Prediction - Tactile

- **FABRICATIONS MATERIAL SUGGESTION PAPERCRAFT.** THE MORE LIKELY A SURFACE POINT WILL BE TOUCHED, THE MORE STURDY THE PAPER CAN BE NOT TO BREAK
- **FABRICATIONS MATERIAL SUGGESTION** THE MORE LIKELY A SURFACE POINT WILL BE GRASPED, THE SOFTER **THE 3D PRINTED MATERIAL** CAN BE SO COMFORTABLE TO GRASP
- **RENDERING PROPERTIES SUGGESTION** (SUCH AS SHININESS AND AMBIENCE PROPERTIES) OF 3D SHAPES BASED ON THE COMPUTED SALIENCY VALUES



Screwdriver, 6 discreet parts and materials

3D ATTENTION-DRIVEN DEPTH ACQUISITION FOR OBJECTS IDENTIFICATION

3D Attention Model for 3D Shape Recognition (View-based)

- **Reconstructing the scene while online** identifying the objects from among a large collection of 3D shapes
- **A 3D Attention Model selects the best views and informative regions to scan from** in each view to focus on, to achieve efficient object recognition
- **The effectiveness is demonstrated on an autonomous robot (PR)** that explores a scene and identifies the objects to construct a 3D scene model

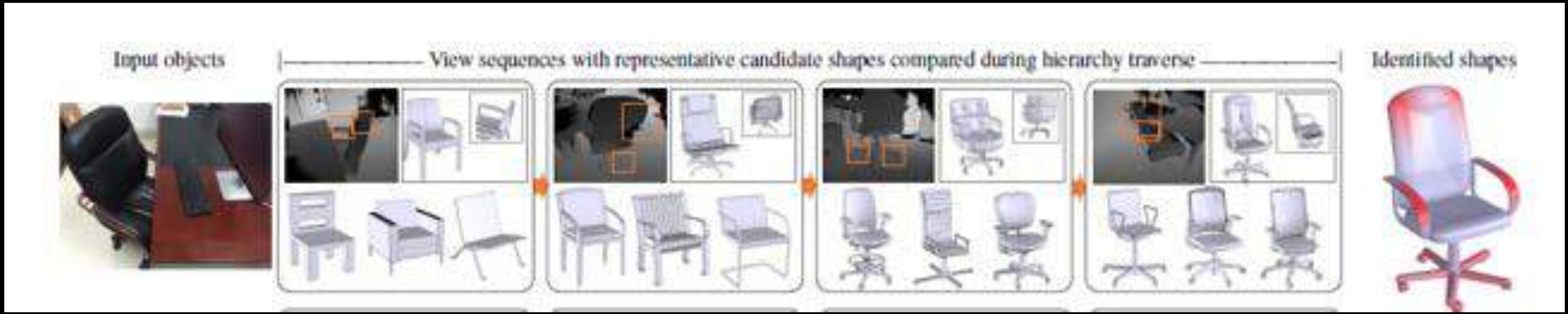
Depth camera on robot , Scanned, object identified from 3D database, driven by attention, retrieval of 3D models

Hu et al., 2016

3D ATTENTION-DRIVEN DEPTH ACQUISITION FOR OBJECTS IDENTIFICATION

3D Attention Model for 3D Shape Recognition (View-based)

- 3D ATTENTION MODEL FOR OBJECT IDENTIFICATION -- TWO LEVELS OF ATTENTION
- **THE FIRST LEVEL SELECTS THE NEXT-BEST-VIEWS (NBVS)** FOR DEPTH ACQUISITION TARGETING AT AN OBJECT OF INTEREST, **WHILE THE SECOND CONCENTRATES ON THE MOST DISCRIMINATIVE REGIONS IN EACH VIEW** FOR PART-BASED RECOGNITION
- BOTH LEVELS ARE TRAINED USING SYNTHETIC 3D MODELS, FOR OBJECT CLASSIFICATION



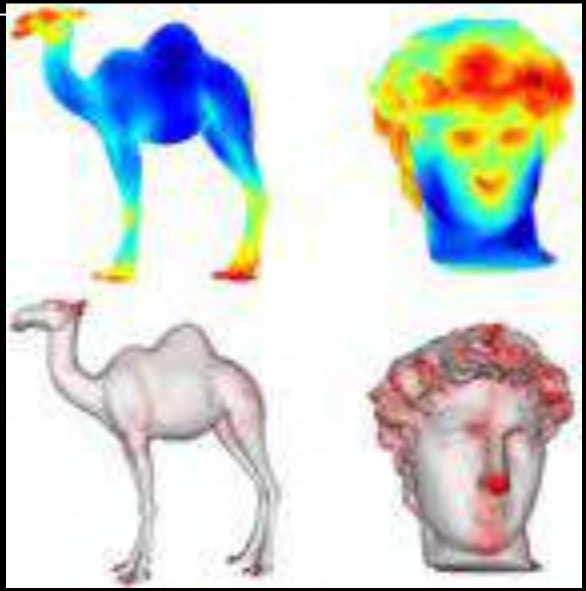
Hu et al., 2016

Acquired depth images, identification, attention, output

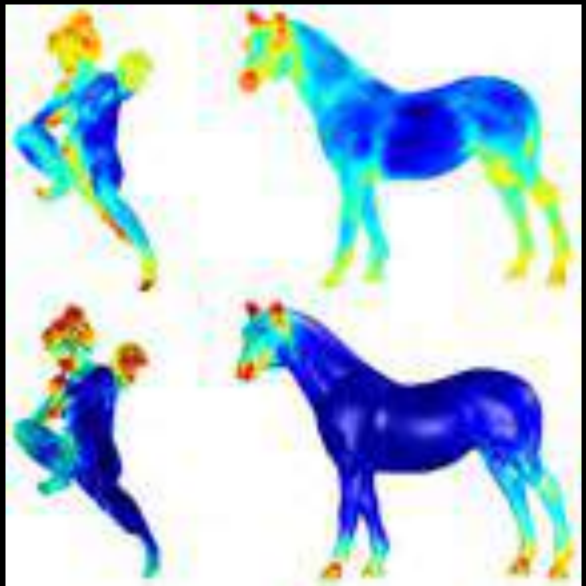
MESH SALIENCY VIA SPECTRAL PROCESSING

Gaze Prediction – Detecting Mesh Saliency

Top spectral
Bottom Chen et al 2012
Eyes nose mouth



- PERCEPTUALLY-BASED MEASURE OF THE IMPORTANCE OF A LOCAL REGION ON A 3D SURFACE MESH
- **INCORPORATING GLOBAL CONSIDERATIONS BY MAKING USE OF SPECTRAL ATTRIBUTES OF THE MESH**, UNLIKE METHODS ON **LOCAL** GEOMETRY
- THE **LOG- LAPLACIAN SPECTRUM OF THE MESH** ARE FREQUENCIES SHOWING DIFFERENCES FROM EXPECTED BEHAVIOUR CAPTURING SALIENCY IN THE **FREQUENCY DOMAIN**
- **INFORMATION ABOUT FREQUENCIES IN THE SPATIAL DOMAIN** AT MULTIPLE SPATIAL SCALES TO LOCALISE SALIENT FEATURES -- OUTPUT FINAL GLOBAL SALIENT AREAS



Top spectral
Bottom Leifman et al 2012
Eyes and feet

Song & Martin 2014

GAZE DIRECTION

IN-MANGA ELEMENTS, WEB DESIGNS