Outatime: Using Speculation to Enable Low-Latency Continuous Interaction for Mobile Cloud Gaming

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Background: Cloud Gaming

- oProcessing and rendering done on cloud
- oClient sends inputs, receives rendered images
- **oBenefits**
	- oBetter graphics use server's processing hardware
	- \circ Easy to develop no compatibility issues

The Problem

oLacks *real-time interactivity*

oHigh latency sensitivity affects gameplay

oBuffering impossible due to changing user input

Fig. 1 (a) – Standard Cloud Gaming: Frame time depends on net latency

Solution

oSpeculate frames until next response

oChallenges – dynamism and sensitivity

Fig. 1 (b) – Outatime: Frame time is negligible

Outatime Architecture

Fig. 2: Outatime Architecture

Speculation for Navigation

oCreate discrete time Markov Chain \circ Define input $N_t = \{\delta_{x,t}, \delta_{y,t}, \delta_{z,t}, \theta_{x,t}, \theta_{y,t}, \theta_{z,t}\}$ \circ Given input n_t , find most likely input for next frame \widehat{N}_t $t+1$ \circ For RTT λ :

$$
\widehat{N}_{t+\lambda} = argmax[p(N_{t+1}|N_t = n_t) * \prod_{i=1}^{\lambda-1} p(N_{t+i+1}|N_{t+i})]
$$

oAlso track error estimate

Speculation for Navigation

- oSupersampling Collect data as fast as input device allows
	- oImproves accuracy
	- oReduces sampling noise
- oPrediction accuracy improves over 5 min. of samples
- oUse training data of other players oCharacteristics depend on skill level

Fig. 5 – Error distribution for different training periods

Speculation for Navigation

oVideo Shake

oCaused by small prediction errors at low-latency oFixed using Kalman Filtering

oKalman Filter oEmphasizes measured values for low RTT (< 40ms.) oEmphasizes predicted values for high RTT (> 40ms.)

Misprediction Compensation

oImage-based Rendering

oTransform rendered prediction to be more accurate

oClipped Cube Map

oRender areas surrounding frame in case they are needed

oLimit size based on expected error values

Clipped Cube Map

Fig. 7 – Cube Map Example

Image-based Rendering (IBR)

Figure 6 – Image-based Rendering in Fable 3

Speculation for Impulse Events

oMuch harder to predict

oSolution: speculate different possibilities in parallel

oCreate speculative input sequence

oAs RTT increases, speculative sequence space grows exponentially

oTwo methods to decrease speculative sequence size oSubsampling

oTime-Shifting

Subsampling and Time-Shifting

oSubsampling

 \circ Sample inputs at a period $\sigma > 1$ clock tick

 \circ Reduces state space to $2\overline{6}$ λ

oOn its own, likely to miss samples

oTime-shifting

oShift every input activation to occur on the nearest subsample

oSolves problem of subsampling

oCan shift inputs backwards since state is speculative

Speculation for Impulse Events

oNot all inputs are binary

oAlternate firing for a weapon

 \circ State space grows quickly (eg. 3^{λ} instead of 2 λ)

 \circ Outatime supports ternary and quaternary events for RTT \leq 128ms

oSome impulse events delay tolerant oDo not speculate oInstead, use time compression to account for RTT delay

Checkpoint and Rollback

oSupports page-level and object-level checkpointing oDepends on density of Simulation State Objects (SSOs)

oPage-level checkpointing oCopy page on page write oInvalidate mis-speculated data oCopy back on rollback

oObject-level checkpointing

oUse inverse functions when rolling back

Implementation

oManually modified Doom 3 code

oDoom 3 master with multiple speculative slave versions orender

- oundo
- ocommit

orendercube

oUsed hardware to improve compression and video encoding

Experiment

o3 Experiments oDoom 3: 23 people oDoom 3: 18 gamers oFable 3: 23 people oMeasured on 3 metrics: oMean Opinon Score

oSkill Impact

oTask Completion Time

Results

oMinor decrease in quality for latencies up to 128 ms oMore noticed by gamers oLarger/faster movements cause greater mispredictions oMay be more sensitive as a player to such effects oSignificant reduction in skills at higher latencies oTask completion relatively unaffected oImprovement over regular cloud gaming

Results

Figure 11: Impact of Latency on User Experience

Figure 12: Remaining Health

Figure 13: Task Completion Time

Performance

oBandwidth 1.97x higher than standard cloud gaming 01.04 Mbps at RTT = 128ms

oFramerate = 52fps at 95th percentile

Strengths and Weaknesses

oStrengths

oMany useful and practical tactics to minimize bandwidth

- oEffective and varied predictive measures are taken for different classifications of inputs
- oProvides foundation to make cloud gaming practical with relatively low latency

oWeaknesses

- oDoes not seem scalable to games with many inputs or fast inputs (eg. RTS)
- oRequires significant code restructuring
	- o Harder to use on existing games
- o Does not consider faster framerates
	- o Modern games are frequently 60Hz

Reference

[1] Lee, Kyungmin, et al. Outatime: Using speculation to enable low-latency continuous interaction for mobile cloud gaming. *Proc. of MobiSys*. 2015.

Questions?

Image Source:<http://i.ytimg.com/vi/gCSmykwODqA/maxresdefault.jpg>

Prediction Summary. Roll (θ_z) is not an input in Doom 3 and need not be predicted.

Figure 4: Prediction for Yaw (θ_x) , the navigation component with the highest variance. Error under 4° is imperceptible.

Figure 8: Angular coverage of 99% of prediction errors is much less than 360° even for high RTT.

(a) Visible Smears

(b) Patched Smears

Figure 9: Misprediction's visual artifacts appear as smears which we mitigate.