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The impact on player experience in augmented reality outdoor games of different noise models

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ABSTRACT

Augmented Reality (AR) gaming is leaving the lab and entering the general population with a combination of high-end systems from the likes of Microsoft and Facebook as well as magic window AR games for commodity smartphones like Pokemon Go. Unlike traditional video games, AR games must solve the registration problem to map objects in the real world to the screen via the camera. Sensors are typically employed to provide the real world pose of the physical camera. However, like all sensors, the location and orientation sensors are subject to noise processes. While the interaction between noise processes and player enjoyment has been studied in networked games, limited work has been done examining the impact of sensor noise on player enjoyment in AR games and that work has been largely confined to simple noise models. In this paper, we present an empirical analysis of the impact on location based AR games of GPS noise on player experience. Our analysis shows that different games are impacted differently by noise. Multimodal noise processes can have a lower impact on player experience than equivalent unimodal processes, when players can time their interactions.

1. Introduction

Augmented Reality (AR) is a technology where digital artifacts are superimposed on a real world view to provide a more engaging, useful, or enjoyable merging of the digital and real. With the advent of high-end consumer technologies such as Microsoft's Hololens [1], or the Oculus Rift [2], and with compelling titles like Pokemon Go [3] available for commodity handsets, AR technology and games are poised for mainstream adoption. Based on the success of early entrants into the space, entertainment and game companies will likely look to expand their offerings to include AR titles for both high and low end systems. However, the technology underlying AR requires several techniques that are not broadly understood in industry and have not been fully studied in academia.

At the center of the AR input stack is the requirement to solve the registration problem, a canonical problem in computer vision and robotics, where the coordinates of an object in digital space (as a rendering or model) must be mapped to real physical coordinates or vice versa. For AR games in particular, the position and orientation of the phone's camera must be measured and translated into virtual coordinates so that digital artifacts can be appropriately rendered. In AR games, the physical camera or cameras replace the virtual cameras more familiar to game developers. If the locations of all cameras in both physical and virtual space are known, then digital objects can be rendered according to camera transforms. To determine the six degree of freedom (x, y, z, yaw, pitch, roll) pose of the camera, a suite of sensors is typically employed.

In AR games, the pose of the camera determines how well the players will be able interact with the digital game characters. Because the primary outcome of a game is User eXperience (UX) or more particularly PX (Player eXperience), ensuring a sufficient Quality of Service (QoS) from these sensors is crucial. A sufficiently noisy QoS could disrupt the rendering of the digital artifacts by misplacing those artifacts in the rendered scene. The term QoS most often referrers to the data transmission quality when considering task performance over the network. However, because different kinds of sensors provide services to the game and sensor quality impacts the quality of an AR game, QoS is an appropriate term to describe the utility of sensors for a particular game. While UX is utilized to assert usability, the PX reveals the enjoyment of the gameplay [4]. Snchez et al. explains UX is an insufficient term to analyze the quality of video games as UX is limited to functionality. According to their word – "In other words, the Player Experience (PX) could be much more complex than the UX. It entails to extend and complete formally the UX characteristics with players dimensions (user and group) using a broad set of attributes and properties in order to identify and measure the experience of players playing a video game, PX. These properties indicate to us whether a game is 'playable or not that is, they will identify the Playability of the video

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game." [4] John Ferrara has demonstrated a model of PX that contains five elements of PX – motivation, meaningful choices, balance, usability, aesthetics [5]. He also mentioned two sub-contents for each of these elements that is required in short-term and long term play duration. While describing the fun of gameplay, Ferrara stated – "Those qualities can't be designed directly, but rather emerge from the experience when all of the elements work together well. Conversely, fun dies when any of the planes haven't been adequately addressed." In this work, we use the term UX to describe overarching usability concerns as well as interface-specific functional concerns, and PX to describe the emotional outcome of play.

Built-in sensors available on mainstream commercial devices are subject to noise disruption leading to potentially erroneous mappings between the real and virtual environments. While experiences in other genres, for example, on-line first person shooters, has demonstrated some degree of player tolerance for inconsistencies in position mapping, such as jittering players due to lag, at some point the introduction of noise degrades player experience [6]. For AR games, accurate pose estimation is vital as Player Experience (PX) is the primary outcome of any video game. Understanding the degree to which noise impacts experience, how different types of noise impact experience, and how different mechanics are more or less susceptible to this sensor noise would be beneficial to game developers and designers.

For studios developing AR games, understanding how noise can affect user experience is critical for designing game mechanics and interface designs which ameliorate or hide the impact of noise. Furthermore, companies wishing to cross develop titles for both high-end HMD, and lower power, but ubiquitous, smartphones should understand the tradeoff between aiming techniques and interface type, to allow for smarter development paths which achieve the highest possible user experience across systems with the smallest amount of code refactoring.

Game designers have proven themselves skilled in hiding the limitations of input devices ranging from traditional controllers to more sophisticated motion capture systems like the Kinect. However, absent guidance on the degree and magnitude of sensor noise impacts on user experience, designers are forced to adopt a risky and expensive trial and error approach.

Although a handful of papers have been published on this issue, they were limited to simple zero mean Gaussian noise models [7–9]. While this noise model is appropriate for some sensors such as accelerometers, other sensors such as GPS, can have patterned noise (e.g. white noise or colored noise) due to atmospheric conditions, and may be disrupted by naturally occurring interference such as buildings, trees, or geographical features.

Because sensors such as GPS can have different patterned noise triggered by various factors [10], in this experiment, we intended to investigate the impact of PX under different patterned noise models containing different scales of noise while playing location-based AR games that use GPS as the location sensor. We hypothesize that patterned or multimodal noise profiles will be more difficult for players to adjust to than single mode Gaussian noise, as stronger disruptions will occur irregularly, and be harder for players to anticipate and compensate for. We developed a system which could inject different types of noise into sensor streams in Android, and compared noise level with player experience as measured by the PANAS and IMI inventories [11,12], which have been widely used to evaluate player and user experience in games [13–18]. The interaction between noise and experience was probed using controlled experiments. We applied repeated-measure MANOVA (Multivariate Analysis Of Variance) to determine the impact of noise model on experience (PANAS) and aspects of motivation (IMI), particularly competence and effort.

In this paper, employed two noise models: a unimodal Zero Mean Gaussian Noise Model (ZMGNM) – a canonical model in sensor systems, and a multimodal noise process generated from a Sequential Noise Model (SNM). By conducting controlled experiment, we compared the impact of different noise models on player experience for games featuring different inputs and narratives. By modifying the operating system, we can deploy any publicly available AR game as a potential experimental testbed, dramatically decreasing the development overhead. Furthermore, we are able to ensure that the games tested are of commercial quality, as they can be downloaded directly from the Android store. By conducting a controlled experiment with two commercial and one academic AR game – all of which employ GPS location as their primary game input – we demonstrated that different noise models can impact the location-based AR games with different input in different ways. Based on the final outcomes, guidance for the AR game development community and other researchers in this arena are provided.

2. Literature review

Video games are a logical application of AR, as blending fantasy and reality has been a goal of game designers for many years. AR games have been the subject to academic research and commercial development. We provide a thorough background on the academic games and a brief overview of relevant commercial games here for completeness.

2.1. Research games

Early work in AR games focused on understanding how technology could be leveraged for different play or educational experiences. ARQuake [19] was the first location based AR game that used GPS, digital compass, and fiducial vision-based tracking to convert the desktop version of Quake to a mobile AR game, played with a laptop, haptic gun, and an HMD (Head Mounted Display). AR characters were deployed using ARToolkit [20]. Similar to ARQuake, Human Pacman [21] is a location based AR game, focused on collaboration among the team members in a virtual 'Pac-World'. Epidemic Menace [22] is a cross media game with several different interfaces such as game board station, a mobile assistant and augmented reality. Players must find a virus that is spread by an evil scientist. TimeWarp is played outside [23] where the virtual characters passively provide information and do not demand any player interaction. Mad City Mystery [24] establishes the idea of learning through location-based AR games. While technical limitation were noted in many of these works, explicitly characterization of the impact of input degradation on player experience was not addressed.

A body of more recent work has focused on AR tagging of locations for educational or artistic purposes. Donald Richardson explored the potential of a location-based AR game as a language learning tool [25]. Koutromanos and Styliaras introduced a location-based AR game – 'The Buildings Speak About Our City' that was specially designed for primary school children [26]. Arkenson et al. introduced a location-based game 'Tag and Seek' that acts as a traveller's guide in Titan City of Taiwan using Near Field Communication (NFC) tags [27]. 'Street Art Gangs' is a hybrid pervasive location-based game played with a mobile phone app, allowing gangs of competing players to tag geo-locations [28]. The design and evaluation of storytelling location-based game 'GEMS' is demonstrated by Procyk and Neustaedter [29]. The players receive prompts from game narrative from their former activities and a geo-located digital memory is created visitable by the other players. Typically these games focus on educational outcomes and take input performance as given.

Other researchers have investigated the role of AR in other educational experiences. Casual adventure game Energy Saving [30] scaffolds player awareness on reducing energy use. GARLIS [31] (Game-based Augmented Reality Library Instruction System) provides for AR interaction within in a real world library. The game play centers on a character who provides information regarding the Chinese library classification scheme. The Table Mystery [32] is a collaborative AR game for exploring chemistry, where each group in the game receives instructions from character with amnesia. GenVirtual [33] is an educational musical AR game designed for people with learning disabilities. Burke et al. described three aspects of AR games (meaningful play, challenge and conservative handling of failure) for limb-stroke rehabilitation named Shelf Stack [34].

Researchers have investigated how novel or newly commoditized technologies can create new experiences. Technologies such as smart phones, table top display and virtual realty headset (e.g. Oculus Rift, Microsoft Hololens, Google Glass) have enhanced AR gaming research variants. The potential of touch-less approach in AR games has been explored by Zhihan et al. where Google Glass was employed [35]. Table-top AR games usually depend on fiducial markers for AR rendering. Lee et al. [36] presented the augmented reality squash game using 'estimated geometric information of images' taken using a stationary camera. The game AR2Hockey (AR AiR Hockey) [37] is a collaborative real time AR game demanding both high fidelity and high response rate from the input sensors. Like ARSquash, AR Tennis [38] is a face to face collaborative AR game. Using 3D sound as an effective parameter, Chatzidimitris et al. introduced a location-based game 'SoundPacman' that conveys game information with engaging gaming experiences [39].

2.2. Commercial games

As is common in games, industrial research and development has driven innovation. Niantic in particular has published location-based AR games of note. In Pokemon Go [3] real locations on Earth contain Pokemon. Once a Pokemon is found a simple orientation-only AR minigame is instantiated, allowing the player to catch the Pokemon. In Ingress [40] the geo-based competition is primarily between the two cliques rather than between individual players.

Most other commercial AR games are based on stationary aiming mechanics. Sky Siege [41] is an AR shooter game played with iPhone. The player's goal is to shoot virtual helicopters and earn points. Star Wars Arcade: Falcon Gunner [42] is a similar game with TIE Fighters instead of helicopters. DroidShooting [43] is a shooting game made for Android Platform, where the player shoots waves of virtual android robots. In AR Invaders [44] and Dimension Invaders [45] the player shoots virtual spaceships. All of these games employ sensors to determine the orientation of the screen for aiming. Skeeter Beater [46] is a casual game demanding lower aiming accuracy. The players need to kill the mosquitoes by locating them with the camera, then tapping. AR-Soccer [47] and AR Basketball [48] are simple casual AR games inspired by popular sports.

2.3. GPS performance

Accuracy and precision are the most commonly used terms to describe GPS measurement quality. Accuracy is expressed through Distance Root Mean Squared (DRMS), Circular Error Probability (CEP) and R95 [49], and corresponds to how closely the sensed signal matches the position in the real world. Moen et al. described telemetry collar that uses GPS readings to locate animals and demonstrated that at least 50% of locations are expected to be within 40 m in uncorrected mode GPS, and within 5 five meters in differential mode GPS under an ideal scenario. However, the frequency of reliability of location readings decreased under interruptions such as within a forest canopy. The authors calculated both the uncorrected and differential mode and compared the precision [50]. GPS signal structure was discussed by Spiker, who demonstrated that if the Root Mean Squared (RMS) position error is less than 10 m, a better performance is achievable [51]. Langley discussed different kinds of GPS receiver noise including thermal noise, antenna noise, and system noise [10].

2.4. Player experience

Quality of Experience (QoE) is an assessment from the user perspective of how well/easily the application meets their needs. The term QoE is broadly used in the sector or networking or telecommunication while User Experience (UX) is more commonly used in Software Engineering and Human Computer Interaction (HCI) areas. An extension of UX is Player Experience (PX) which is particularly used in game research. The measurement of enjoyment during gameplay is examined while considering PX for a particular video games. The psychological impact of playing games can be significant. Playing games can impact the player both physically and emotionally. The game world takes a player to the virtual world to 'live' the life [52]. For example, games require players to make decisions, and take actions accordingly. Still, the inquisitive nature of human might always demand the answer of 'why do we actually play games?' [52] The first and foremost answer appears to be- 'having fun.' Rigby and Ryan [52] defines 'fun' as a very broad and superficial word in gameplay. Rather, they preferred to shift the 'fun' to 'need satisfaction' that includes – competence, autonomy, relatedness, consistency and density.

Self Determination Theory (SDT) [53] is an established physiological theory that is used to evaluate PX in game experience research [15,54,55]. One of the mini-theories of SDT is called Cognitive Evaluation Theory (CET) [15] illustrates players' intrinsic motivation based on competence and autonomy. According to Birk and Mandryk – "intrinsic motivation (IM) is defined by a locus of control inherent in the person, and an outcome attributed to volition and achievement" [15]. The Positive and Negative Affect Schedule (PANAS) [12,56] is one of the most widely used scales to measure mood or emotion of the user. PANAS and IMI (Intrinsic Motivation Inventory) [11] surveys, standard instruments for evaluating user experience in games. Both IMI and PANAS have been used previously to evaluate PX in game research [13–18]. The detail of measurement scale used for this research is described in Section 4.2.

Competence is an intrinsic need satisfied by achieving mastery in game. Higher levels of competence could be achieved with optimal challenges and feedback. While competence improves the mastery of accepting challenge, autonomy enhances the power of performing actions in game. According to the authors – "feeling autonomous means that we are pursuing things that interest us and that we want to pursue. By contrast, we feel controlled when we are not interested in what we are doing and are simply taking action as a stepping stone to some other goal." With limited choices, games could be autonomous if the players find it interesting. Relatedness is the reflection of meaningful connection combined with competence. The relatedness leads to consistency to achieve the destiny of the game. According to authors – "Because of this immediate ability to bring people together in shared worlds, video games supply a novel and efficient vehicle for people to experience relatedness." All these intrinsic motivation factors of players during gameplay can be analyzed through PENS (Player Experience of Need Satisfaction). The authors also examined how PENS [52] can impact on larger spectrum of personal such as vitality and well-beingness of the broader game community The PENS scale is an important tool in this thesis.

Most research on the impact of noise processes on player experience have focused packet jitter in networked games. Player experience has been shown to be impacted by this noise. Anastasia et al. investigated how network delay affects player experience in cooperative games when interaction with shared objects are required during gameplay. The authors demonstrated that delays over 100 ms significantly decrease player performance and jitter negatively affects user performance [57]. Henderson and Bhatti noted that in spite of lower QoS, networked games are popular [58]. The authors performed an experiment to examine players' tolerance towards the QoS and showed network delay affects player's decision to join a game server. Aline et al. investigated the impact of latency and jitter upon players' frustration, enjoyment, performance and experience [59]. Their findings demonstrated that constant play is not impacted until 300 ms of delay (no jitter) although with an addition of jitter to a delay of 200 ms, players' experience was affected.

A more limited body of work has highlighted the impact of noise on AR games. Lochrie et al. explored the challenges restricting the wide scale adoption of augmented mixed reality games due to sensor error [60]. The authors identified low quality of augmentation as the main factor affecting location-based AR gameplay experience. Later, they proposed an iterative design approach to improve the play experience of such games. Eishita and Stanley have experimentally explored the impact of sensor noise in AR games from a number of perspectives [7–9]. These three experiments demonstrated that player experience is deferentially impacted with the presence of noise in different genres of AR games. However, only ZMGNM was explored in these experiments.

3. Methodology

In this work, we wish to replicate one of our earlier experiments, but employing a more nuanced noise model. To test the impact of the more sophisticated noise model, we ran similar experiments to [8] and used the same modified Android system and games as a test platform. Each of these games employs a simple location based mechanic, where GPS and orientation sensors are used to determine the pose of the phone in space; however, only the GPS location was corrupted by artificial noise. Each of these experimental apparatuses are outlined in the following sections.

3.1. Noise model

To compare the outcome of UX under different noise models, two models were developed - Zero Mean Gaussian Noise Model (ZMGNM) and Sequential Noise Model (SNM).The ZMGNM is similar to those reported in [61,62,7,8]. ZMGNM is an appealing unimodal noise model, as multiple random noise processes tend to sum to a Gaussian distribution according to the Central Limit Theorem, at least to a first approximation, and because as a zero mean additive process, the original signal can be represented by the mean of the corrupted signal. Four different levels (None, Low, Medium and High) are defined in this model based on different standard deviation (described in Table 1). The procedure to define the numeral value of the standard deviation of different levels is described in experimental detail.

However, some sensors, such as GPS, are not always well characterized by zero mean Gaussian distribution. In fact, the noise characteristics of GPS can vary depending on the proximity to buildings, natural formations (e.g. canyons or mountains) or even the weather. In these cases, the noise itself might still converge toward a Gaussian distribution, but with a different variance than in the case where a user is standing in the open. In geo-science the most common noise models for GPS are White Noise and Colored Noise, including Flicker Noise [63]. White noise is random signal with samples uncorrelated in time (zero mean), similar to our ZMGNM. Colored noise is defined as a random signal with samples that are correlated in time – that is the current noise level depends on the history of noise levels [63].

The simplest model for time dependence is a Markov chain model. In a Markov chain, the model is represented as a sequence of discrete states (in this particular case, each state is a zero mean Gaussian with a given variance), and the probability of moving between those states. When in a state, the model emits a value drawn from the distribution associated with that state. As aforementioned, our system has four independent states of ZMGNM – None, Low, Medium and High – distinguished by increasing variance, shown in Fig. 1. We introduced a multimodal Sequential Noise Model (SNM) which is a noise model that moves between ZMGNM of different variance. For ZMGNM, a single zero mean Gaussian distribution with the defined variance was employed with a unimodal structure. For the multimodal SNM noise levels, each individual state consisted of a single Gaussian with the same variance as the individual level of the ZMGNM – that is, the Low noise state in the Markov chain is a Gaussian with the same mean (zero) and variance as the single distribution used in the Low ZMGNM condition.

Table 1
Standard deviations (σ) for noise levels.

Level	SD(σ) in Degree	SD(σ) in Meter
None	0	0
Low	2.5×10^{-5}	2.77
Medium	5×10^{-5}	5.53
High	10×10^{-4}	11.07

Altogether we defined five different conditions for the experiment as follows -

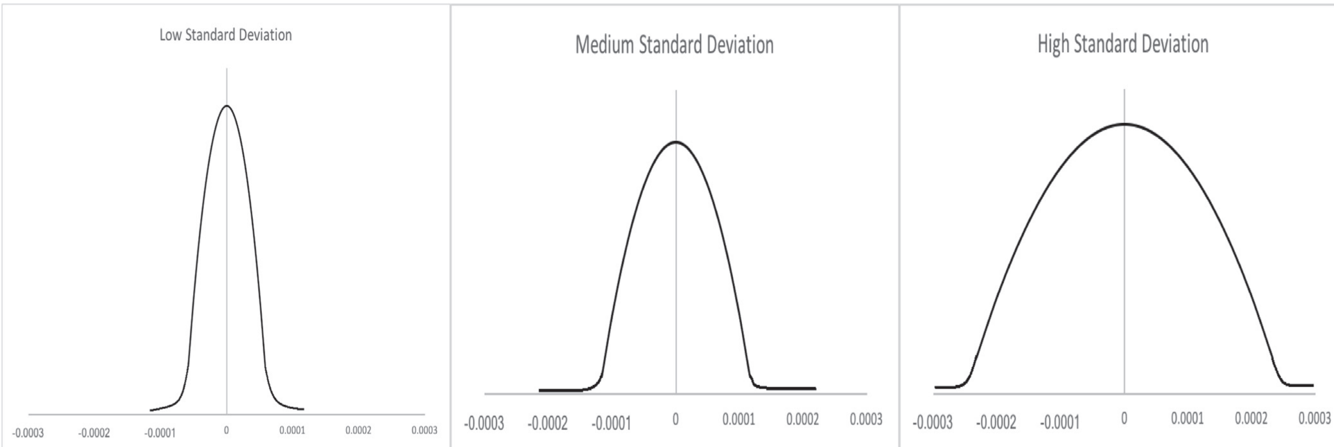
- None – no noise; as a control
- Low and Medium levels of ZMGN
- Average-Low and Average-Medium levels of SNM (the mean variance of the SNM condition equaled the mean variance of either the Low or Medium noise ZMGNM); described in Fig. 2.

In the None condition, no noise is added to the signal, acting as a control. In other conditions, noise values were drawn and added to both latitude and longitude, generating a two dimensional noise-perturbed reading centered on the value returned from the sensor. Because both the models consist of zero mean noise, the average GPS accuracy is not impacted, but the precision of sensed position is perturbed by increasing offsets in the low, medium, and high noise levels. As far as the game engine was concerned, the artificial noise led to a false indication that the player was moving and it attempted to render the view of the digital object with respect to the player's new apparent position. However, from the player's perspective, having not actually moved in real space, the re-rendering appears as motion of the digital asset. To keep our observational data comparable, we deployed the same standard deviations used in [8], shown in Table 1. The standard deviation chosen (through informal testing) for three different noise levels (low, medium, and high) have average values comparable to the variance observed in empirical GPS values in [64]. The standard deviation of each noise condition was calibrated through pilot testing, such that the game was always playable even at the highest noise levels. Several pilot tests were conducted to identify the highest amount of noise variance that could be added to the location signal before the game became unplayable and this noise level became the variance for the High noise level condition. The Medium noise and Low noise conditions were defined as half and one quarter of the High noise standard deviation respectively.

Because GPS positioning accuracy is achievable to up to 10 m on commodity devices [51], we wanted to keep the greatest noise added close to that boundary. The standard deviations in medium and low levels were reduced to half and a quarter of the maximum added noise. If compared with practical scenario, the high noise resembles with the noise that may appear receiving signal while passing through an area with tall buildings. The medium level noise may appear under an area with large trees and finally the low level noise could be an environmental interruption such as bad weather. An open field experimental area was selected to minimize the potential for natural GPS interference.

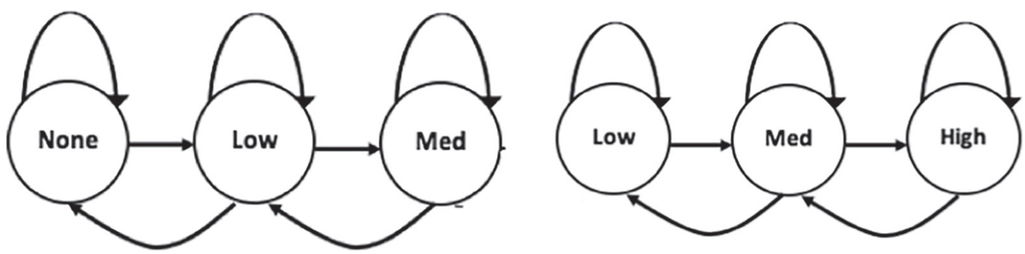
At every iteration the SNM model randomly draws a transition (including self transition) between the different possible states. That is, the model can transition from a low noise to no noise, low noise or medium noise, but not directly from low noise to high noise, as shown in Fig. 2.

For consistency of comparison between the two noise models, we set transitions probabilities, such that averaged over a sufficient number of



(a) Low (b) Medium (c) High

Fig. 1. Noise distribution of Low, Medium, and High Standard Deviation.



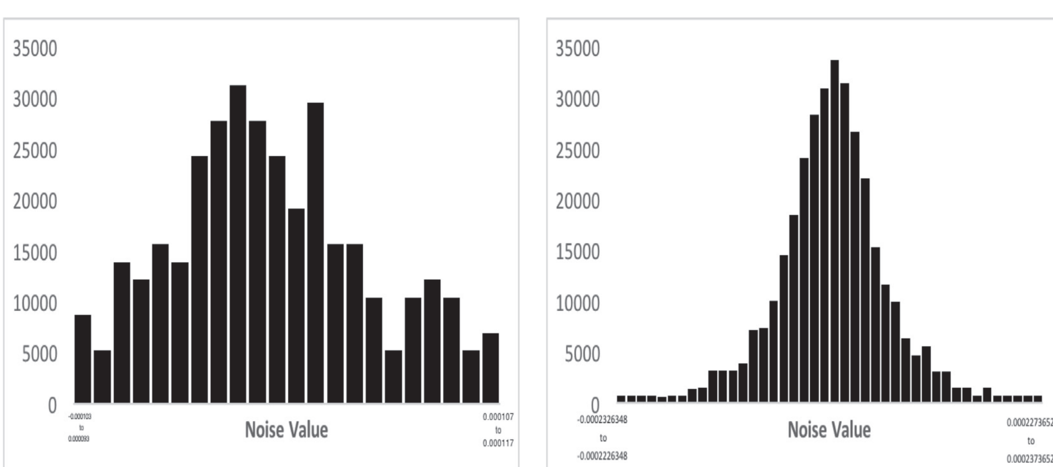
(a) Average-Low (b) Average-Medium

Fig. 2. Sequence of Average-Low and Average-Medium levels of SNM.

samples, the mean variance of the SNM condition approximated the mean variance of either the Low or Medium noise variance ZMGNM. Players would have experienced the same average precision in Average-Low as Low and Average-Medium as Medium, allowing some degree of consistency during comparisons. Because the SNM can enter states where it is more likely to draw larger noise-based offsets (e.g. from the High Noise distribution), correspondingly more draws must be made from the Low noise model to compensate. This behaviour leads the SNM to have lower noise offsets in general, punctuated by periods of larger disruptions as opposed to a similarly-valued ZMGNM which is characterized by a sequence of more consistent moderate noise levels. Fig. 1 shows the standard deviation format used in the noise levels. Figs. 3 and 4 demonstrates the histogram and time series (respectively) of both noise models. Transition probabilities for the tested model are shown in Table 2.

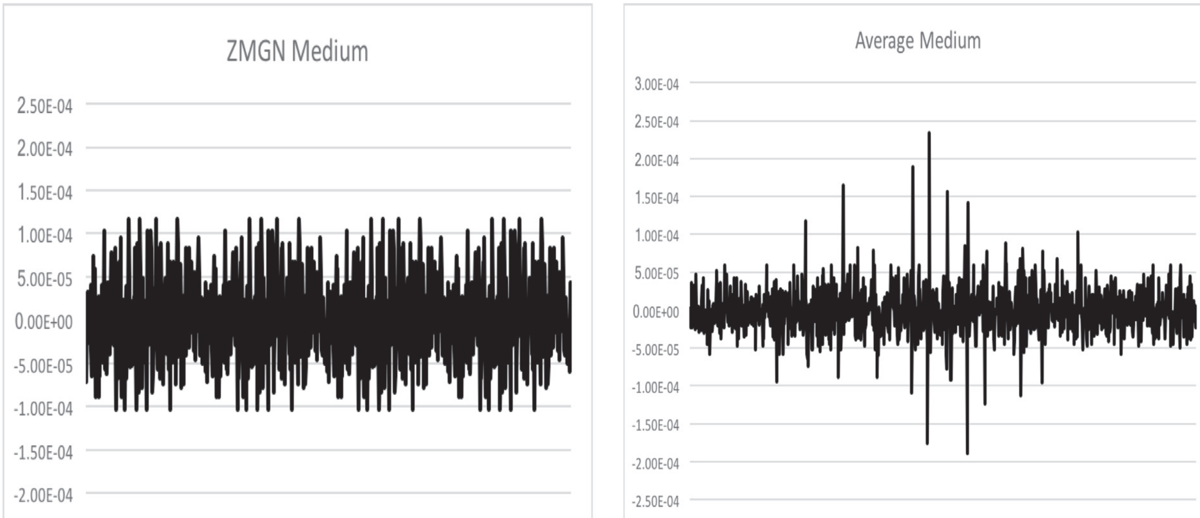
3.2. Game description

Because this experiment is based on the methodology in [8], we chose the same games as an evaluation testbed. Three games were



(a) ZMGNM (b) SNM

Fig. 3. Histogram of ZMGNM with medium standard deviation and SNM of Average-Medium noise distribution.



(a) ZMGNM (b) SNM

Fig. 4. Time series of ZMGNM with medium standard deviation and SNM of Average-Medium noise distribution.

Table 2
Transition probability of noise levels in SNM.

From	To		
	Low	Medium	High
Low	0.5	0.5	0
Medium	0.33	0.33	0.33
High	0	0.5	0.5

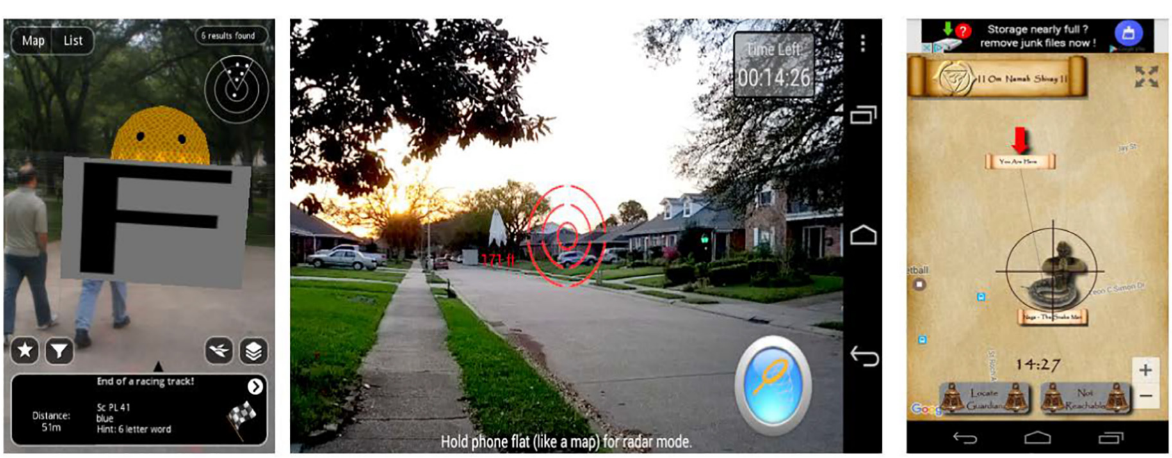
chosen for this experiment. While many AR games exist on the Google App store, only a few use GPS as input (orientation is much more common) and fewer still have sufficient stability and user interaction to warrant testing. After eliminating unsuitable games, we chose two commercial AR games with similar mechanics, but different design, a ghost hunting game and a treasure hunting game. We included an academic edugame based on an Easter egg hunt mechanic as the third game, giving us three games centered on finding a digitally tagged location, but with different interaction mechanics and narrative. The selected games are briefly described in the following subsections. Screen shots of each game are shown in Fig. 5. Table 3 provides summary of the games.

3.2.1. SpecTrek (ST)

SpecTrek [65] is a casual AR game where players hunt for digital ghosts in a given area. At the beginning, a circular play area is defined by selecting a radius. We employed the lowest radius (467 m). A number of ghosts (from 3 to 5, default 3) are randomly placed within the play area and can be located through the map as points of interest (POI). A map interface is visible when the phone is held parallel to the ground. To find the ghosts through camera, the player must hold the phone perpendicular to the ground, as if taking a picture, in the direction indicated on the map. If pointed in the right direction, the digital ghost is displayed. The size of the ghost depends on the distance of the player from the ghost. To catch the ghosts, the players must walk towards the ghost holding the phone in hand. When the player is within 175 m of the ghost's location, the ghost can be caught by aiming the reticule at the ghost and tapping the net located on bottom right corner of the screen.

3.2.2. Temple Treasure Hunt (TT)

Temple Treasure Hunt [66] is a scavenger hunt game where players



PasswARG SpecTrek Temple Treasure Hunt

Fig. 5. Game screenshots.

Table 3
Game descriptions.

Game	Play Area	Time	Target
Temple Treasure Hunt	500 m	15 min	Find treasure guardians
Speck Trek	407 m	15 min	Capture ghosts
PasswARG	450 m	Customized	Find the passwords

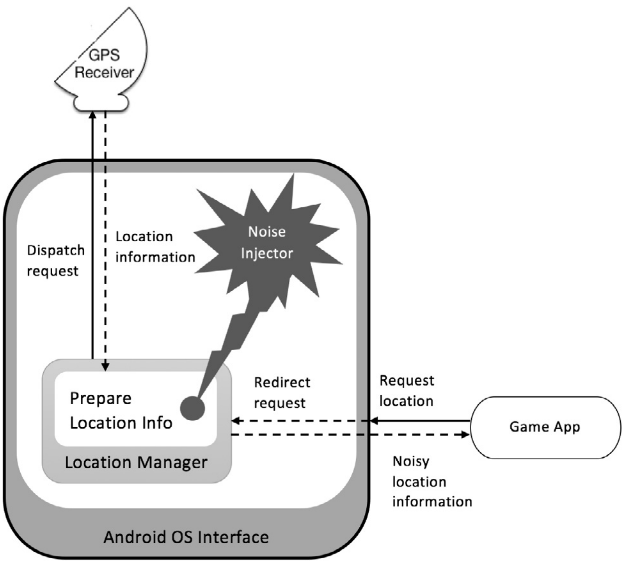


Fig. 6. Android OS manipulation process.

hunt for virtual treasure located at points in the physical world. Similar to SpecTrek, players need to walk towards a POI displayed on a map, visible while the device is held parallel to the ground. Unlike SpecTrek, the digital avatar is not loaded until the player reaches the position of the treasure. Once the label of player's location and treasure matches (demanding higher precision), the digital character is loaded and visible through the AR interface, when held perpendicular to the ground. The last task of the player is to tap on the treasure, completing the level.

3.2.3. PasswARG (PW)

PasswARG [61] is an AR game that employs the Layar reality browser [67] and can be played on iPhones and Android smartphones and tablets. The PassWARG game is based on an Easter egg hunt mechanic, where players navigate a given area to find clues held by virtual characters [62]. Players were given a sentence with a blank word in it. The answer was hidden as a form of scrambled letters. Players search for geo-located digital characters who have the scrambled letters in the form of speech bubbles. Players must physically approach a character for the clue it holds to be visible through the magic window AR. Solving the puzzle by unscrambling the letters reveals a password. A correctly-deciphered password completes the level.

4. Experimental setup

4.1. Software configuration

To implement the noise variation in system, we employed the Android 4.1 AOSP (Android Open Source Project) provided by Google. Because Android is open source, changes can be made to the sensor data serving components of the system. Because of the architecture of Android, this can readily be accomplished by changing a single set of method calls within the appropriate sensor classes. Most Android smartphones or tablets are equipped with built in sensors to measure motion or location. The Android API divides sensors into three major categories: Motion, Environmental and Position. The sensor frameworks are available with classes and interfaces to allow apps to interact with sensor data. However, sensor availability varies depending on API version as well as hardware configuration [68]. This system was initially described in [8].

Our experiments were conducted using GPS sensors. Although most of the motion sensors were defined in the `SensorManager` class, location sensors are located in the `android.location` package and become operational with supported hardware. `LocationManager` is the key component of the location framework. An instance of `LocationManager` needs to be requested from the system with `getSystemService(Context.LOCATION_SERVICE)` call to handle a new instance of `LocationManager`. Noise is added by adding values randomly drawn from as described above within the `getLat()` and `getLng()` method in this class. Apps that employed the sensor then received the noise-corrupted data. Parameters for the Gaussian distribution could be adjusted through a separate app interface, which modified the parameters retrieving values from an array checked by our noise injection module at startup. This process is illustrated in Fig. 6.

4.2. Participant detail and procedure

Participants were required to report to the same area individually and play the games under all four noise levels and the no noise control. The order of games were constant but the order of noise levels within the games was randomized based on a Latin square design. Two rounds of 15 participants (for a total of 30, 27 male and 3 female participants, mean age 29, SD 3.469) took part in the experiment. Prior to engaging in the experiment, players were briefed on the purpose of the experiment and signed informed consent forms, in keeping with the approval from our Ethics Review Board. To allow participants to familiarize themselves with the game, we provided a 2–3 min learning period for players to play the game and ask questions, prior to beginning the experiment. Each play session was limited to 2–3 min. For the SNM levels (Average-Low and Average-Medium), the transition from the previous state occurred randomly in every 5, 10, and 15 s and therefore, 2–3 min of gameplay provided 4–20 state transitions.

After each experimental condition, the play experience was measured using two scales – PANAS (Positive and Negative Affect Schedule) [12,56] and IMI (Intrinsic Motivation Inventory) [11] surveys, standard instruments for evaluating user experience in games. The assessment of players' positive and negative play experience was conducted using the PANAS-X scale where players were asked 20 emotion adjectives. Each of these adjectives were formed in Likert-scale running from 1 (very slightly or not at all) to 5 (extremely). Half of the emotion adjectives were positive and half were negative. Based on the players rating, a combined score (one for positive affect and one for negative affect) was generated. Intrinsic Motivation of the players were assessed using the Intrinsic Motivation Inventory [11] consist with 18 questions [69]. All the items are rated ranged from 1 (not at all) to 5 (quite a bit) on Likert-scale. For example, the player‘s were investigated on a question – "I felt tense while playing" or "Playing the game was fun". Collected response was manipulated to create and overall score along with four scores for each of interest-enjoyment, competence, effort and pressure. Both IMI and PANAS have been used previously to evaluate PX in game research [13–18]. We were not directly interested in the overall intrinsic motivation, but of two of the constructs, competency and effort, as we anticipated that these parameters might be impacted by patterned noise, in keeping with our hypothesis. With practice sessions, play sessions, and survey completion, each game condition took approximately one and a half hours per participant. A demographic survey was administered on the last day of the experiment.

4.3. Design and research question

We wished to investigate the interaction of the two factors (game and noise levels) with PX. Our objective was to analyze whether the PX varies based on the noise levels or noise type for different kinds of location-based AR games. A repeated-measure MANOVA was used to compare the main effects of Game and Noise Levels and the interaction effect between the Game type and Noise Level on players' positive and negative experiences and intrinsic motivation.The two independent variables were Game and Noise Levels. The factor Game has categorical data with three different kinds of location-based AR games (SpecTrek, Temple Treasure Hunt and PasswARG) and Noise Level had five different ordinal levels (None, Low, Average-Low, Medium, and Average-Medium) as conditions.

The dependent variables included Positive and Negative Experiences, Interest-Enjoyment, Competence, Effort and Tension-Pressure. The data type of Noise Level was ordinal and included four experimental groups – Low, Average-Low, Medium and Average-Medium – and a control group where measurement was made without artificially added noise. All effects were considered to be statistically significant. Bonferroni correction was applied to adjust the value of the confidence interval. Later, pairwise comparisons were performed to compare results between groups.

5. Results

Qualitatively, players completed all the games in all noise conditions except for Temple Treasure Hunt where they occasionally had difficulty locating the treasure guardian under high noise conditions. SpecTrek players occasionally expressed difficulties when the ghosts moved quickly. Playing PasswARG was qualitatively unimpeded by noise.

Although Low and Average-Low level noise belong to different noise models, both contains same standard deviation, as do the Medium and Average-Medium levels. Table 4 shows the standard deviations for all noise levels calculated from the aggregated data logged during the experiment. This provides the insight of recording adequate amount of data during the experiment to receive the same standard deviation as defined in the experimental design.

The result of our experiment revealed a significant multivariate main effect for Game ($F(2, 28) = 50.351$, $p < 0.001$, $\eta_p^2 = 0.782$) and Noise Levels ($F(4, 26) = 12.305$, $p < 0.001$, $\eta_p^2 = 0.654$) on players' positive play experience. A significant multivariate main effect for Game ($F(2, 28) = 71.115$, $p < 0.001$, $\eta_p^2 = 0.836$) and Noise Levels ($F(4, 26) = 6.211$, $p = 0.001$, $\eta_p^2 = 0.489$) on players' negative play experience as well. For all factors of IMI, significant effects were observed for both Game and Noise Levels.

5.1. Analysis of PANAS

Box plots showing the results of PANAS analysis are shown in Fig. 7. Here, the whiskers and boxes represent the quartiles, the inner line represents the mode, and the mean is indicated by the small circle. Outliers are plotted as individual points (crosses) on the top and bottom of the upper and lower whiskers. The y-axis in all graphs corresponds to the un-normalized score for the experience parameters according to the survey instrument guidelines.

Table 4
Standard deviations (σ) for noise levels of different noise types.

Noise Level	Noise Type	SD(σ) in Degree	SD(σ) in Meter
Low	ZMGNM	2.5×10^{-5}	2.77
Average-Low	SNM	2.5×10^{-5}	2.77
Medium	ZMGNM	5×10^{-5}	5.53
Average-Medium	SNM	5×10^{-5}	5.53

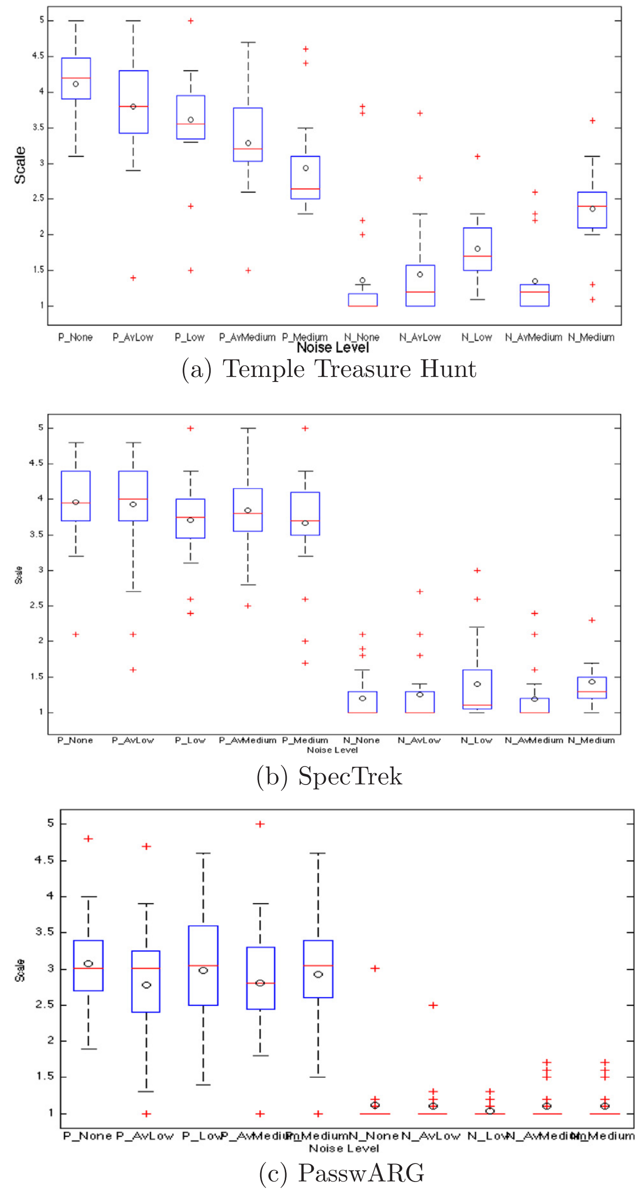


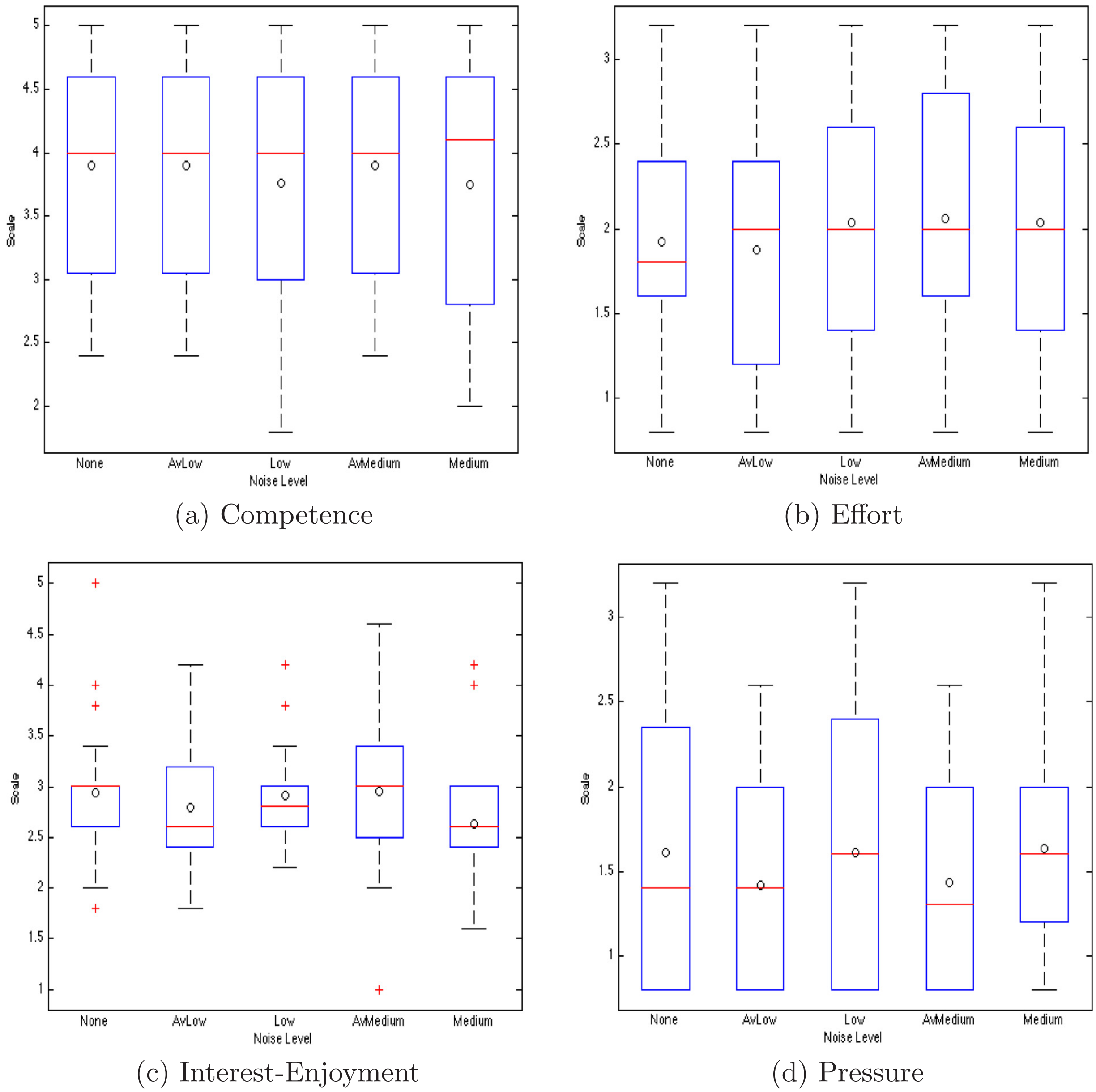
Fig. 7. PANAS of Temple Treasure Hunt, SpecTrek and PasswARG (N = None, L = Low, M = Medium, AL = Average-Low, AM = Average-Medium).

PANAS measures did not display any significant differences for the game SpecTrek under variable noise or PasswARG for all the noise conditions. This is readily apparent in Fig. 7, as the mean of each is clearly within the center quartiles. Significant effects were observed from the PANAS measures for Temple Treasure Hunt.

In Temple Treasure Hunt, players' positive play experience gradually decreased with noise with the best experience in No Noise ($F(4,26) = 17.823$, $p < 0.001$, $\eta_p^2 = 0.733$) while playing Temple Treasure Hunt. However, negative experience remained unchanged with None and both Average-Low, Average-Medium conditions; but increased with existence of Low and Medium noise. In pairwise comparison, effects were significant between Medium-Average-Medium ($p < 0.001$), Medium-Average-Low ($p < 0.001$), Low-Medium ($p = 0.02$) and None-Medium ($p < 0.001$).

5.2. Analysis of IMI

Interesting and significant effects were observed from the IMI



(a) Competence (b) Effort

(c) Interest-Enjoyment (d) Pressure

Fig. 8. IMI of PasswARG.

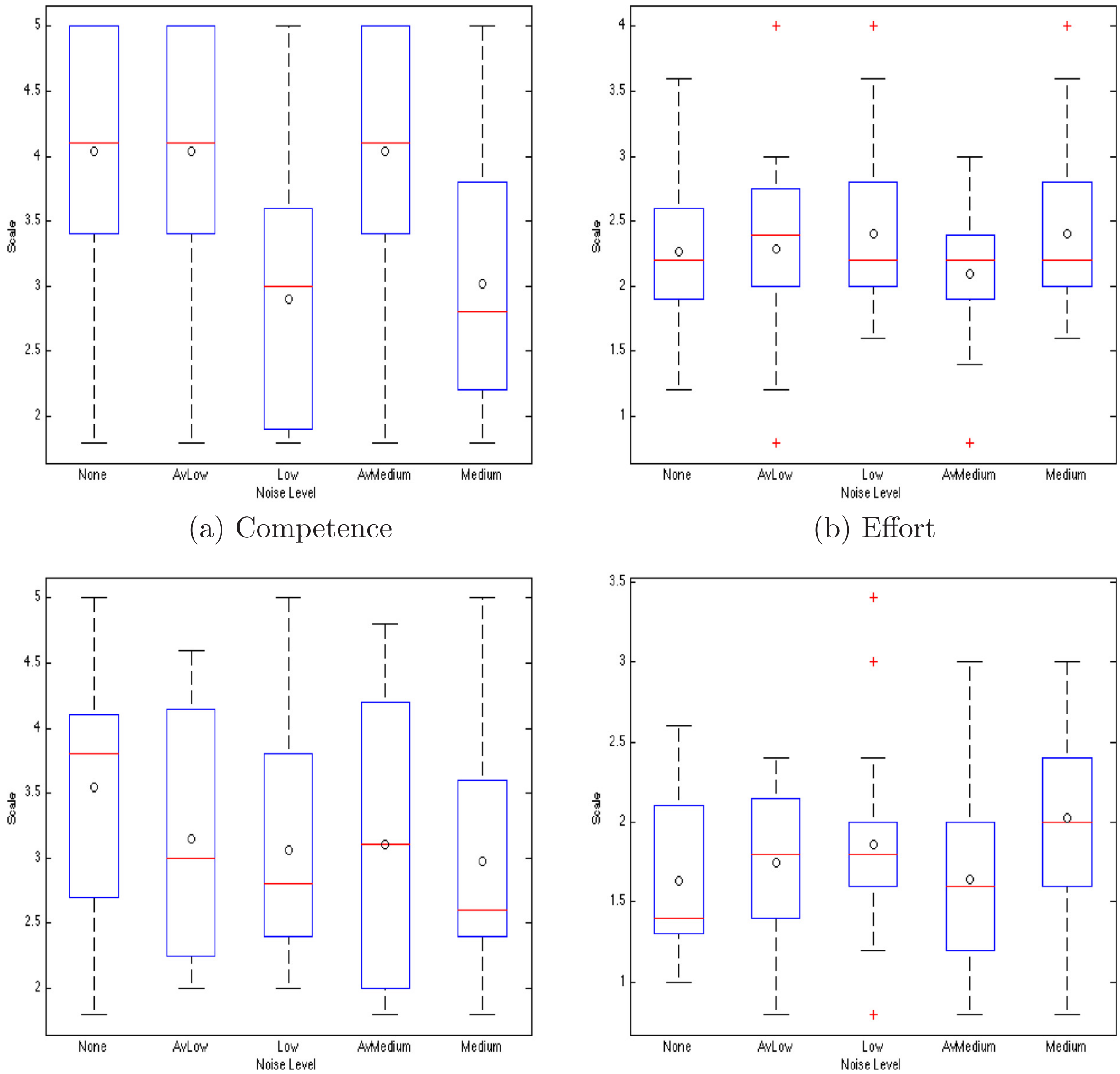
measures for SpecTrek and Temple Treasure Hunt. Figs. 9, 10, and 8 The box plots showing the distributions of responses for competence and interest/enjoyment are shown in these figures. Here, the whiskers and boxes represent the quartiles, the inner line represents the mode, and the mean is indicated by the small circle. Outliers are plotted as individual points (crosses) on the top and bottom of the upper and lower whiskers. The y-axis in all graphs corresponds to the un-normalized score for the experience parameters according to the survey instrument guidelines.

PasswARG demonstrated a consistent play experience for almost all the noise conditions, demonstrating, as noted in [9], that game mechanics, narrative and input modality differentially impact player enjoyment under noisy input conditions. No statistically meaningful significant differences were found for the PasswARG game. PasswARG IMI responses are summarized in Fig. 8.

While playing SpecTrek, only competence varied significantly between different noise models reflected in pairwise comparison. Players felt competent playing the game under the None, Average-Low and Average-Medium noise, and felt significantly less competent under Low and Medium noise. Pairwise comparison demonstrated significance in competence between None-Low ($p = 0.002$) and none-medium ($p = 0.008$). Fig. 9 demonstrate the competence and pairwise comparison of players' competence levels of SpecTrek. The means for the Low and Medium noise are clearly outside of the quartiles of the other distributions, indicating the degree of the effect size.

While playing Temple Treasure Hunt, players had a lower feeling of competence while playing the levels under ZMGNM compared to SNM and No Noise conditions ($F(4,26) = 34.482$, $p < 0.001$, $\eta_p^2 = 0.841$). Pairwise comparison showed that perceived competence was similar to the No Noise and the conditions of SNM having $p < 0.001$ for Medium-Average-Low, None-Average-Low, Medium-Average-Medium, None-Average-Medium, Medium-Low, None-Low, and None-Medium. Similar results were observed for effort. Compared to ZMGNM levels, SNM levels required subjectively more effort to play.

Significance was observed in pairwise comparison of levels between Medium-Average-Low ($p < 0.001$), Medium-Average-Medium ($p < 0.001$), Medium–Low ($p < 0.001$), None-Medium ($p = 0.003$). Unlike competence and effort, interest-enjoyment had no significant



(a) Competence (b) Effort

(c) Interest-Enjoyment (d) Pressure

Fig. 9. IMI of SpecTrek.

difference between ZMGNM and SNM. However, an overall decrease of interest was observed with increase of noise ($F(4,26) = 13.065$, $p < 0.001$, $\eta_p^2 = 0.668$). The pairwise comparison showed significance between None-Average-Low($p < 0.001$), None-Low ($p < 0.001$), Med-Average-Low ($p = 0.04$), None-Average-Medium ($p < 0.001$) and None-Medium ($p < 0.001$). Likewise, pressure tends to increase gradually with noise ($F(4,26) = 11.129$, $p < 0.001$, $\eta_p^2 = 0.631$). The findings of competence and effort seem to indicate that players had higher sensitivity towards ZMGNM than the SNM. However, the outcome of interest-enjoyment and pressure express change of experience with increment of noise. Fig. 10 summarizes the IMI for Temple Treasure Hunt. The limited overlap between the quartiles for Competence and Effort, and the limited overlap for Interest-Enjoyment and Pressure illustrate the magnitude of the effect size in the experiment.

6. Discussion and future work

In our experiment we hoped to determine the differential impacts of noise model on player experience crossed with game narrative and input. Game genre and input modality had an impact as expected from [8], with PassWARG player experience being essentially immune to the noise manipulations. However, Temple Treasure Hunt, and to a lesser extent SpecTrek were impacted by manipulating noise. Consistent with previous work [8], players were more susceptible to higher levels noise in Temple Treasure Hunt because of the sensitivity of the input, and a reasonable expectation that an inanimate object should not move. The validation of earlier results is heartening in and of itself, and provides confidence that the extended analysis reported here is building on a solid foundation. In particular, we noted an additional effect due to the sequential noise model. Even though participants were exposed to the same average noise variance between the Low and AvergeLow conditions, participants reported significantly fewer drawbacks to player experience in the Average-Low condition than the Low condition. This trend held for the Average-Medium and Medium conditions as well.

The results contradicted our hypothesis, in that players tended to report better experiences playing the SNM conditions than the ZMGN conditions. In the SNM, participants were occasionally subjected to lower precision of location information than the equivalent ZMGNM

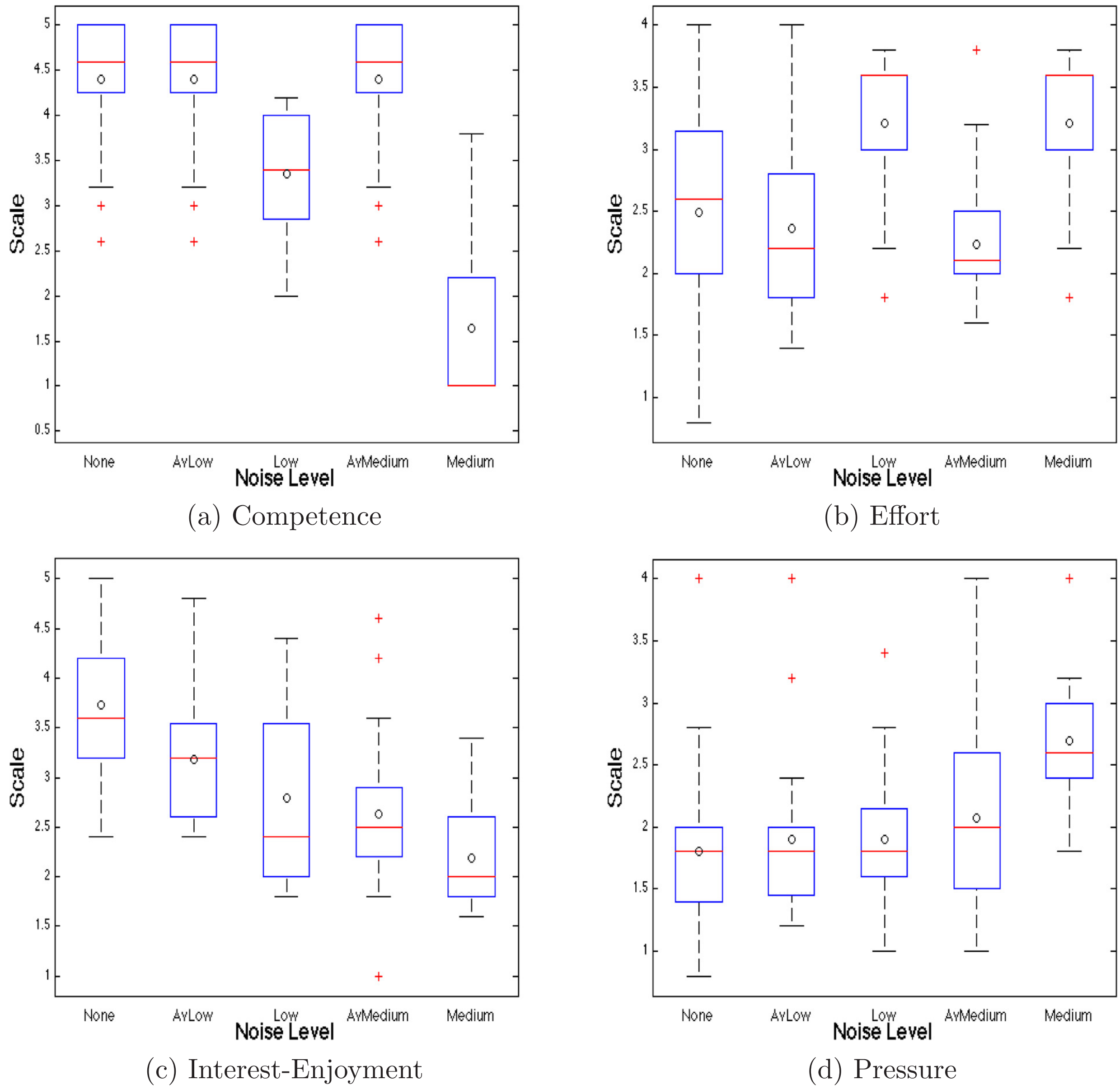


Fig. 10. IMI of temple treasure hunt.

levels. However, to maintain the same average variance as the ZMGN condition, they also had significant periods at higher relative precision. It appears that players were more easily able to reject short periods of low precision, and benefit from the prolonged periods of lower noise. This may be explained by the Peak-End theory proposed in [70]. In Peak-End theory, player experience is dominated by player state at the peak of play, and the end of play, rather than being averaged over the entire play experience. If players were pausing during periods of higher noise variability, and acted during periods of lower noise variability, then the key player experience windows (the Peak and End) would have occurred during periods of lower noise, and the player experience would have been more consistent with having played in a low noise environment.

This interpretation provides some hope to GPS-based game designers, as player experience should reflect the play which occurs during low noise periods, as long as the game design permits players some freedom in selecting when to interact. In all of the games examined here, there were no timing mechanics attached to the interactions – the treasure did not disappear on a timer and the ghost did not shoot back, allowing the player to pick the best time to interact. If the player were forced into peak or end interactions during high noise variability episodes, we would not expect the lower noise regime's experience to dominate. A significant design finding from this work is that players can benefit from systems with variable noise behaviors, but only if they have sufficient timing freedom to determine under what noise regimes peak and end experiences occur.

This experiments described here have made a significant contribution towards the AR game development community. Nevertheless, some limitations exist. The participants recruited were biased towards university community and male. Only GPS sensors were evaluated, and only simple selection mechanics within the games. Additional and more complex game mechanics should be considered in future work. Finally, we primarily used commercial games. While this does provide a minimum level of polish and code stability, it also limits the opportunity for telemetering the games. These effects should be investigated in custom games including more fulsome telemetry to probe the extent to which Peak-End hypothesis is reflected in gameplay. If we are correct, most play actions should be recorded as happening during periods of lower noise in the SNM conditions.

7. Conclusion

In this paper, we have presented a novel approach for investigating the differential impact of sequential noise in comparison with ZMGNM upon user experience in different location-based AR games. By modifying the sensor services in the operating system to provide structured noise disruptions following both Gaussian and sequential noise patterns, we conducted a controlled experiment with three different kinds of AR games which employed GPS as their primary input. After performing a user study, we found that depending on game design, narrative, and interaction technique, the players' experience varies deferentially for Zero Mean Gaussian and Sequential Noise Models. The findings also demonstrated, that player experience was less sensitive to variable noise than the equivalent Gaussian noise. In the future we intend to investigate new games, sensors and demographics to understand the generalizability of these findings.

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