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Short Paper

Art-directing Appearance using an Environment Map Latent Space

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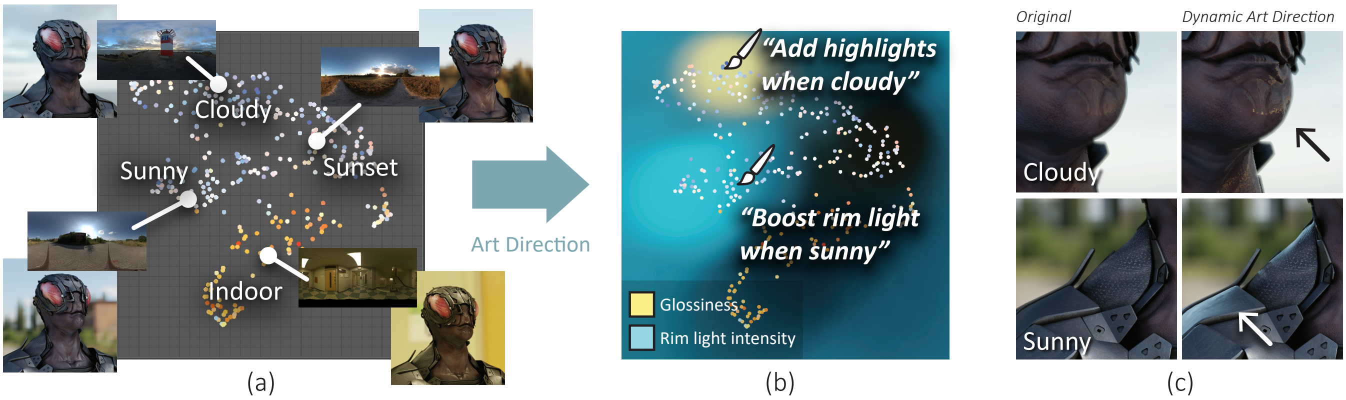

Figure 1: *a) Our environment map (EM) latent space expresses semantic clustering in 2D, for navigating a varied EM database during look development. b) Art directing material and lighting edits across the space is achieved by 2D painting. c) Art-directed appearance is preserved in similar EMs, and dynamically adapted to changing environment lighting. Character model by Emiliano Colantoni (CC BY 4.0).*

Abstract

In look development, environment maps (EMs) are used to verify 3D appearance in varied lighting (e.g., overcast, sunny, and indoor). Artists can only assign one fixed material, making it laborious to edit appearance uniquely for all EMs. Artists can art-direct material and lighting in film post-production. However, this is impossible in dynamic real-time games and live augmented reality (AR), where environment lighting is unpredictable. We present a new workflow to customize appearance variation across a wide range of EM lighting, for live applications. Appearance edits can be predefined, and then automatically adapted to environment lighting changes. We achieve this by learning a novel 2D latent space of varied EM lighting. The latent space lets artists browse EMs in a semantically meaningful 2D view. For different EMs, artists can paint different material and lighting parameter values directly on the latent space. We robustly encode new EMs into the same space, for automatic look-up of the desired appearance. This solves a new problem of preserving art-direction in live applications, without any artist intervention.

CCS Concepts

• ***Computing methodologies*** → ***Dimensionality reduction and manifold learning;*** *Rendering;*

1. Introduction

Look development (look-dev) is the task of verifying that a 3D model gives acceptable appearance when rendered under different lighting environments [ZO14]. For this task, artists use lighting environments captured from the real world [KBG*15], for high quality pre-visualisation. These lighting environments are captured as high dynamic range (HDR) 360° panoramas called environment maps (EMs) [Deb06]. During look-dev, an artist will render a 3D model with its material properties under many EMs with varying types of illumination (e.g. indoor, outdoor-sunny, outdoor-overcast, etc.) to verify adequate shape and material depiction.

This material may give acceptable appearance in some lighting conditions, but not in others. For example, artificial rim lighting may be desired in sunny scenes but not in cloudy scenes. Glossy highlights may need exaggeration in cloudy scenes, but not in sunny scenes. Different EMs call for unique appearance edits, de-

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termined by a director's stylistic intentions [Bou04]. Unfortunately, artists currently can only assign a fixed set of material parameters.

To mitigate this problem, manual art-direction edits can be made in offline films, at the cost of artists' time and effort in post production. However, dynamic 3D games and augmented reality (AR) applications feature unpredictable and large variation in environment lighting, such that a fixed appearance cannot give satisfactory results under all possible lighting. For these situations, appearance edits need to be pre-defined in pre-production, and then automatically adapted to real-time environment lighting changes during runtime. There currently exists no workflow for artists to specify customised appearance variation across many EMs.

We propose a new workflow to address this problem, using a novel latent space of EM lighting. We learn a 2D latent space from a large and varied database of EMs. Our space visualises semantically meaningful clusters for several types of lighting conditions (indoor, sunny, overcast), in a single 2D plot. The visualisation is firstly used in look-dev, to browse and identify which EM types require appearance editing. Artists can then prescribe the desired appearance edits, unique to different EM clusters in the space. In our interface, artists can use 2D painting appearance parameters values for different clusters in the space, and control the parameter's interpolation between the clusters. We then automatically adapt the artistic edits made for each EM to unseen environments in live applications. This workflow is shown in Figure 1.

Using the latent space for browsing provides meaningful categorisation of the 1000s of EMs used in visual effects studios. Previous EM organisation methods either require manual labelling [KSH*14], or infer semantic information [XEOT12] irrelevant to lighting properties. Our learned 2D organisation avoids time-consuming probing of higher dimensional spaces when browsing and selecting points using multiple 2D subplots [LdAJ18; EDF08; SW12]. Unlike these higher dimensional spaces projected into 2D, our space allows per-EM, appearance edits by providing a unique 2D location for all EMs.

Many previous art-directable rendering techniques also allow artists to edit appearance, but only in a single scene [SPN*16]. Stylisation using illumination guides assumes that lighting is unchanged [FJL*16]. Parametric appearance edits can been transferred under slight lighting changes [HLR*17], but cannot take unique edits made for different EM types as input. We instead require appearance edits to interpolate between more drastic lighting variation found in large real-world EM databases. Our latent space allows artists to adopt ubiquitous 2D interfaces such as painting to control how shader parameters vary for different lighting types. To preserve the edits we can consistently encode unseen EMs into the same space, and simply look up the lighting and material values previously painted on the space, for similar EMs. We focus on real-world EMs as they are the most common EMs used for look-dev. In summary, we make the following contributions:

- We learn a 2D latent space with semantically meaningful clusters that express several types of lighting conditions in a single plot.
- We support consistent embeddings of unseen EMs to allow edits to automatically adapt to lighting environment changes.
- Artists can control (via painting) the transition of material and synthetic-lighting edits between environment types.

2. Related Work

Previous work in EM database organisation used manual labelling [KSH*14]. While semantically meaningful, this is prone to human error and is impractical for large databases. Texture classification algorithms have been used to categorize panoramas [XEOT12; KSH*14]. This provides encoding of scene content (with labels such as "beach", "church", hotel room", etc). These labels lack light source information such as shadow softness, colour, and light direction. More importantly, human-assigned labels with subjective descriptions can be inconsistent. This motivates organising EMs based on mathematical features that retain meaningful to artists. SkyBrowser [CLH*14] provides a four-dimensional feature space, but focus on textural and colour-based features for sky images. Mathematical texture features were shown to provide little benefit for lighting tasks [GSY*17].

Several prior works provide techniques to parameterise EMs into low-dimensional representations. Spherical harmonics [RH01] and Haar wavelets [NRH03] provide compact descriptions of arbitrary lighting but in terms not meaningful to artists. In this work, we use spherical harmonics [RH01] as a feature for distance measuring between EMs, rather than the descriptor itself. This is similar to previous comparison metrics for 3D shape analysis [FMK*03].

Dimensionality reduction has been relied upon to learn latent spaces and 2D data visualisation [EMK*19; MH08; Jol11; MHM18]. 2D latent spaces have been used in artistic applications [BA06]. Marks et al. [MAB*97] introduced the concept of design galleries to aid user parameter selection by embedding high-dimensional outputs into a 2D visualisation. Hermosilla et al. [HMRR19] learn a latent space to map 3D scene representations to rendered images. Chalmers et al. [CZR20] introduce the 'Illumination Space', a lighting-based five-dimensional feature space for organizing EMs. However, we require an 2D artist-interpretable space supporting hand-editable mappings between real-world lighting and art-directed appearance.

Lalonde et al. use dimensionality reduction for 2D visualisation of learned EM features for low dynamic range (LDR) [ZL17] and HDR outdoor data [HAL19]. However, their HDR dataset embedding is limited to outdoor EMs. Their LDR embedding includes indoor data but does not spatially separate these from outdoor EMs. Our method achieves separation of indoor and outdoor EMs in 2D.

Regarding art-direction during look-dev, there is limited research in remapping appearance based on illumination. Previous techniques support artist editing of renderings [SPN*16; Pel10; OMSI07], but are limited in supporting dynamic lighting variation. X-toon [BTM06] also uses a 2D interface for artists to remap shader parameters with respect to two rendering attributes at a time, though do not support several semantic EM attributes all at once. The patch-based synthesis work StyLit [FJL*16] provides user defined mapping between physically based shading and stylisation, though only for one lighting environment. The parametric appearance edits of Hennessey et al. [HLR*17] the types of EMs for which the edit should be applied to cannot be specified.

3. Method

We describe our method starting with learning the latent space, by embedding a training dataset of EMs in 2D. We then describe our interface for art-directing appearance for different EM clusters, and preserving art direction in new EMs.

3.1. Data Preparation

We collate existing indoor and outdoor EM datasets from Dutch-skies [Dut], HDRI-Hub [HDRb], HDR-Maps [HDRc], and Weber et al. [GSY*17]. We arrive at a training dataset of 350 EMs after balancing the number of available indoor and outdoor samples. We first horizontally rotate all EMs to center-align them by their dominant light (DL) azimuthal angle. We detect the DL direction by filtering noise and detecting the peak intensity for each EM and align them based on their DL's azimuthal angle. This separates the DL azimuth angle as an independent variable from the latent space. Two EMs with similar lighting but different horizontal rotation, are thus considered to be similar. Artists can still rotate the EM in the final rendering. We do not align the DL elevation as it is often correlated with sky colour and lighting softness from atmospheric scattering, in outdoor environments. Similarly in indoor EMs, artificial ceiling lights and natural light from windows are typically found. Aligning the DL elevation also tilts the horizon, producing unnatural lighting.

3.2. Learning the Latent Space

We use the recent manifold learning method UMAP [MHM18] to reduce the dimensionality of the training dataset into a 2D space. For this resultant 2D space to have semantically meaningful axes and clusters, UMAP requires a distance function that can compute the similarity between two EMs. We define this distance function using a combination of the EM's spherical harmonics (SH) coefficients [RH02], and its mean colour in LAB space [dlEc78].

Rather than using all pixels in the EM, we use SH to remove texture detail. We compute SH coefficients up to the 5^{th} band, enough to capture high-frequency details to differentiate between hard, soft, and multiple lighting. We compute this for each of the red, green and blue channels in the EM resulting in 75 features from SH decomposition for each EM.

Although we compute SH for each colour channel, we would like the distance function to differentiate colours in the EM as a human would perceive them. Hence, we use the mean colour (or first SH band coefficients) of the EM in LAB space as an additional feature. We divide the SH coefficients by their total ℓ_2 norm to normalise intensity variation in the EMs, and divide the LAB values by 100 (maximum luminance value) for comparable ranges between SH and LAB. The euclidean distance between the concatenated SH and LAB feature vectors is used as the distance metric to compare EMs in the UMAP embedding.

We then need to choose how important we consider the SH coefficients over mean LAB colour using a weight w_{SH}. For example, if LAB is given a large weight over SH, then EMs will primarily be compared by their average colour rather than directional lighting properties. This would result in the embedding to lack separation of varying lighting properties. Furthermore, the LAB feature itself already provides a low-dimensional space, being only three values.

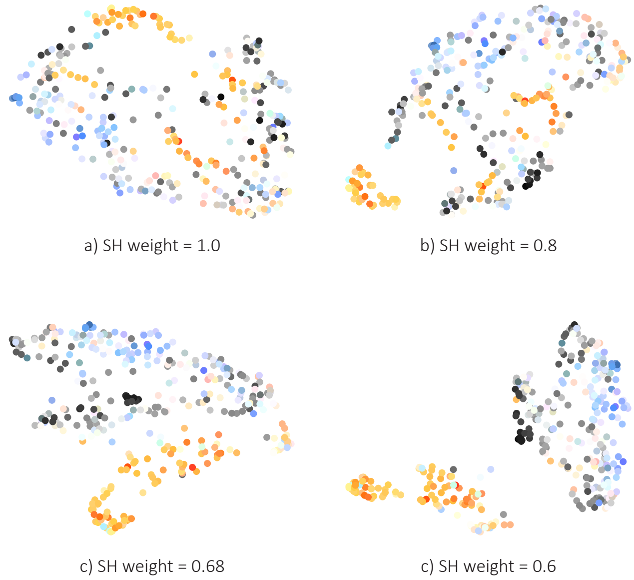

Figure 2: *Embedding results with each EM plotted with its mean RGB colour. a) Using only SH ($w_{SH} = 0$), indoor EMs (mostly warm colours) and outdoor EMs (mostly cool colours) are embedded too close together. b) Weighting SH by 0.8 leads to a slight distance increase, but not meaningful clustering. c) Weighting SH by 0.68 successfully forms a distinct indoor EM cluster, while preserving sunny and overcast clusters. d) If w_{SH} is too high, the embedding is biased toward colour and devalues lighting properties.*

Empirically we see that the LAB feature helps to increase the distance between indoor and outdoor environment maps (EMs) in the 2D feature space. In Figure 2 we show that increasing the influence of LAB over SH features helps distance indoor EMs from outdoor EMs, which enables better clustering. Hence we set w_{SH} to 0.68 clusters the indoor EMs separately while minimally biasing the embedding towards a purely colour-based arrangement. We use PCA to verify that our chosen w_{SH} maximises variance across two dimensions (see analysis in the supplementary materials).

3.3. Art Directing Appearance Using the Latent Space

Having learned the 2D organisation of EMs, we use a 2D painting interface for artists to vary appearance parameters, of their choice, across the space. In our interface, we map an image texture for each parameter to our space, such that is spans all points in the embedding. We overlay the embedding, on top of the texture. Artists can then paint the desired appearance parameter values for different EM clusters, directly on the space. Artists can choose to art-direct any parameter in the 3D editor (including material, lighting, colour grading, and compositing). They can paint intensity values for scalar parameters, or in colour for RGB colour parameters.

UMAP simultaneously learns the encoder with the previous embedding. We leverage this encoder to embed new EMs, unseen during training, into the same learned clusters. To preserve art-directed appearance in a new EM, we compute its SH and LAB features (as in Section 3.2) and encode them into the latent space. We use the new EM's location in the space, to look-up the scalar intensity values painted in the texture. We apply the sampled parameter values in the rendering. We show an example of this application in the next section, after examining the latent space.

4. Results

After embedding the training set with respect to our SH and LAB colour distance metric, we examine the learned latent space for semantically meaningful organisation. Figure 3 gives an overview of the observed spatial organisation expressed by the embedding.

We firstly observe that our method organises EMs by their light elevation along the x-axis. The elevation of the dominant light in the environment decreases as the x-axis increases. This places sunset skies on the right of the space, as the elevation of the sun is low. Similarly, indoor scenes are also consistently organised by the elevation of their dominant light source in the scene.

Secondly, we observe clustering of EMs into three semantic categories outdoor overcast, outdoor sunny, and indoor. These clusters are spread across the y-axis, while maintaining the same ordering of light elevation across the x-axis. Outdoor overcast EMs that cast uniformly soft shadows are concentrated at the top region of the space. Outdoor sunny EMs with hard directional shadows are typically found in the middle. The indoor EMs are found below the sunny cluster. These environments typically have multiple artificial lights, or a mixture of artificial and natural lighting from windows.

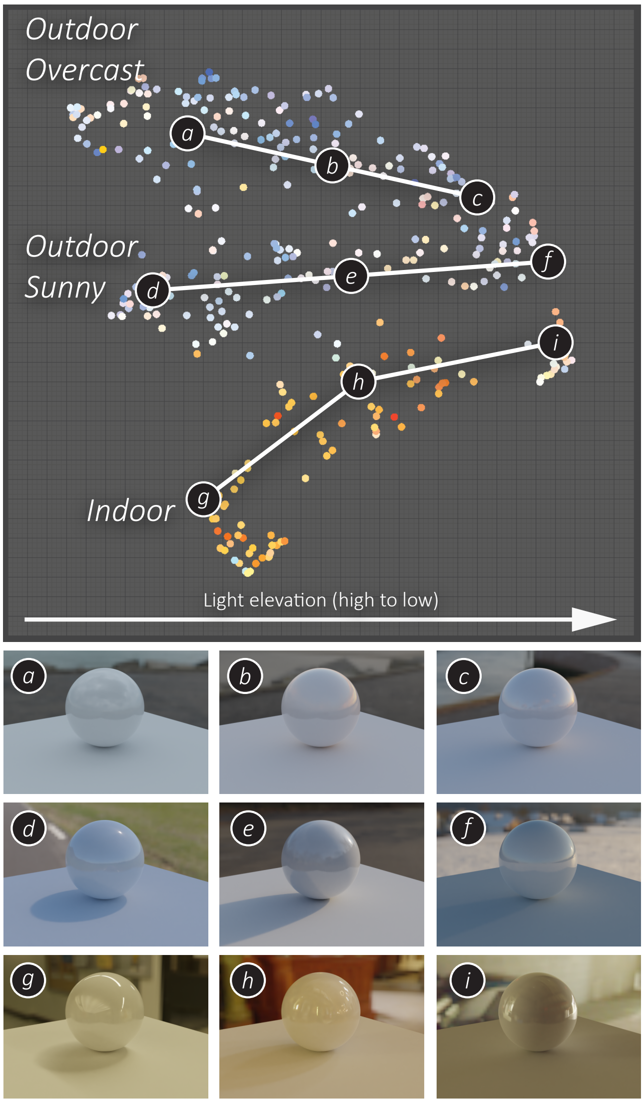

Figure 3: *Latent space EMs plotted as points coloured using their mean RGB colour. We observe overcast, sunny, and indoor EM clusters shown by soft, hard, and multiple shadows, respectively, rendered below. Light elevation (seen in highlight positions and shadow length) varies consistently across the clusters in the x-axis.*

4.1. Evaluation

We show that the latent space has distinguished semantic clusters, and that it can reliably embed new points into these clusters. We validate both properties of our space by embedding a human-labelled test set of EMs unseen during training. Using EMs not originally included in the training verifies that unseen EMs are embedded into the appropriate clusters.

Although our space expresses some examples of nuanced semantic clustering (e.g. indoor with natural light, or separating clear and cloudy overcast skies) we evaluate the expression of high-level clusters that are not as ambiguous. We clarify these high-level observed clusters with the following labels: overcast, sunny, indoor-artificial, indoor-natural, and night (see supplementary materials for their definitions).

We also make distinctions between environments that do not clearly fall within these categories. Indoor environments with mixed artificial and natural, with no clear dominant lighting type, are considered ambiguous (e.g. room with both a large window and bright ceiling light). Outdoor EMs with poorly captured dynamic range (incorrectly representing the brightness of the sun) are also excluded as they may be sunny but cast soft shadows.

Excluding these ambiguous cases, we proceed assuming that our definitions for outdoor sunny, outdoor overcast, and indoor categories are indisputable by humans. Hence we evaluate using the labels given by the providers, without collecting multiple labels for the same EM. We manually label all unlabelled EMs and verify that all existing labels conform to our definitions.

We collate a test set of 262 outdoor and 80 indoor EMs (after discarding ambiguous cases) from the same sources as the training set, but not used during training. Unseen EMs are encoded by extracting the same spherical harmonics and LAB mean colour features of each EM, as explained in Section 3. We encode the EM features with the transform procedure of UMAP (without retraining), and examine the new EM positions in the latent space. In Figure 4 see that the same observed clusters are expressed in the test

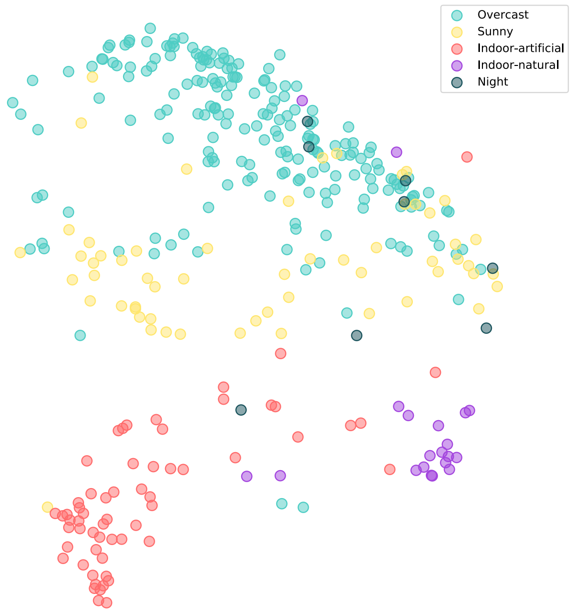

Figure 4: *Encoding a test set of unseen EMs into our latent space. The new samples are concentrated in the same clusters observed in the original embedding.*

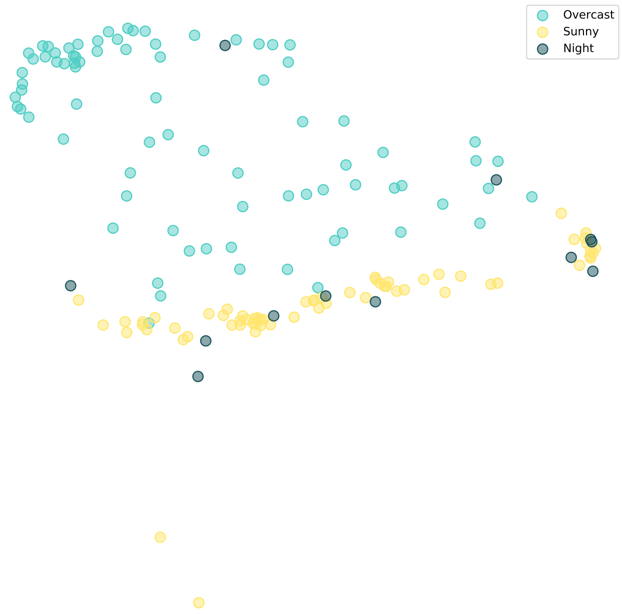

Figure 5: *Encoding unseen EMs from the HDRI-Haven outdoor dataset [HDRa]. The new samples are concentrated in the same clusters observed in the original embedding.*

set embedding. Although night scenes were under-represented in both test and training sets, we see they appropriately appear in at least one outdoor cluster. The night EMs that were embedded in the sunny and overcast clusters, had hard and soft lighting respectively. Night and sunny scenes are not semantically similar, but the night EMs still embedded into outdoor clusters with matching lighting softness. The overlap between clusters is attributed to noise in the encoding process due the stochastic nature of UMAP. We see only a few points located in the wrong clusters which we consider outliers. This is a limitation of our method as we do not enforce the learning of assumed labels during training.

We also test the quality of embedding samples from the HDRI-Haven outdoor dataset [HDRa] (156 samples after filtering) in Figure 5. We see that these are embedded in the expected location, even though our training set did not contain any samples from the HDRI-Haven vendor. This also shows that our encoder is robust to outdoor environments with capturing processes different to those found in our training set. We also see much clearer semantic clustering such as the much narrower sunny cluster. This could be because the EMs from this vendor have much greater dynamic range than those used during training. Within the overcast cluster of this embedding, we find EMs with full cloud or building cover of the sun, located at the top. Then we see a transition to EMs with partial cloud or tree cover of the sun when moving down toward the sunny cluster. Like the first test set, outdoor night scenes are also encoded into at least one outdoor cluster. Only two outliers are found in the indoor cluster. It took between 1 and 2 seconds to encode the test datasets into the latent space. This time was measured on a laptop with an i7-4700MQ 2.4GHz CPU, with 16GB of RAM.

4.2. Art-direction Application

We apply our latent space as an appearance control space for use during look-dev. We used a real-world look-dev use-case from Blender Animation Studios. The example character in Figure 1-a was lit under several different lighting environments to verify consistent appearance. In Figure 1-b, the artist could increase the skin material's glossiness to restore highlights. Using our latent space, artists can find which kind of EMs give problematic appearance. By simply painting intensity values in the latent space, artists can indicate under what lighting conditions should the glossiness be increased, and by how much. As shown in Figure 1-c, the highlights are emphasised in cloudy environments, while the rim light is boosted in sunny environments. This is because the artist painted high glossiness values in the cloudy cluster and high rim light intensity values in the sunny cluster.

Having shown the latent space reliably encodes unseen EMs, such art-directives will be automatically adhered to in the similar future scenarios. This removes the need for repeated appearance edits and automatically preserves art-direction in games, and live AR applications. In the supplementary material we show an example appearance transition between EM types, as painted by an artist.

5. Conclusion

In this paper we addressed the problem of adapting appearance edits to changing environment lighting. We do this by learning a 2D latent space of EMs. We have shown that, even in 2D, our latent space expresses semantic clustering without using explicit categorical labels. Our 2D space allows artists to use painting operations to art-direct appearance attributes for different environment lighting. Having shown consistent embedding of new EMs (e.g. using estimated EMs for AR [GSY*17; ZL17]), these artist directives can then be automatically preserved for all similar EMs encountered in live game and AR applications. While we show separation of outdoor and indoor EMs, indoor EMs with multiple lights casting both hard and soft shadows are not clearly clustered in our space. In future work we would like to cluster EMs into more categories.

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