Evaluating Dynamic Surface Compensation for Robots with Projected AR

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Abstract

Projector-based augmented reality (AR) enables robots to communicate spatially-situated information to multiple observers without requiring head-mounted displays. However, they require flat and weakly textured surfaces to project onto; otherwise, the surface needs to be compensated to retain the original projected image. Yet, existing projection compensation methods may not work in complex, textured environments when robots must navigate.

In this work, we evaluate state-of-the-art deep learning-based projection compensation on a Go2 robot dog in a search-and-rescue scene with discontinuous, non-planar, strongly textured surfaces. We contribute empirical evidence on critical performance limitations of state-of-the-art compensation methods: the requirement of pre-calibration and inability to adapt in real-time as the robot moves, revealing a fundamental gap between static compensation capabilities and dynamic robot communication needs. We propose future directions for enabling real-time, motion-adaptive projection compensation for robot communication in dynamic environments.

Figure 1: A robot dog in a commonly-seen search-and-rescue scene with textured and non-flat surfaces. Projecting on such surfaces requires compensation to correct geometric and photometric distortions. In this work, we contribute empirical evidence for state-of-the-art compensation performance.

CCS Concepts

• **Human-centered computing → Systems and tools for interaction design**; • **Computer systems organization → Robotics**.

Keywords

Projector-robot system, Projector compensation, Projector-camera system, Augmented Reality, Human-Robot Interaction

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1 Introduction

For robots to work effectively with people, they must be able to communicate task-related information and their intent clearly to gain trust and acceptance. Human-robot interaction (HRI) researchers have traditionally investigated non-verbal means, e.g., gesture [13, 43], eye gaze [1, 36], sound [61], visual display [49], light [3], and verbal speech [50]. However, real-world interactions are highly contextual and often involve specific objects and locations in the physical world. When communicating about spatially situated targets in cluttered scenes, traditional modalities such as gesture, gaze, and speech can lack precision and clarity, while low-fidelity sound and light signals are less expressive, and on-robot displays suffer from limited viewing angles and legibility at a distance.

To enable robots to communicate spatially situated objects, researchers are increasingly leveraging augmented reality (AR) [16, 42, 51, 54, 55]. AR spatially registers 3D virtual content onto the physical world, allowing visualizations to be situated where they are relevant, also known as situated visualization [44]. Applied to robotics, for example, AR allows robots to precisely externalize motion intent, e.g., manipulation and navigation trajectories directly in the task space, e.g., which object it refers to [8, 19], perceived or to be manipulated [42], or which path it will navigate for both ground robots [20] and drones [56]. Results have shown improved safety during navigation, with participants choosing alternative paths [11], increased comfort, and motion intelligence [59]. Recently, AR virtual appendage was even perceived more anthropomorphic [21], activating familiar human-human interaction patterns.

Yet, we risk losing these benefits that AR offers to robotics due to a major scalability issue associated with the popular headset-based AR displays. They require each viewer to wear a headset, which is

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often impractical for a crowd of people in a group and team context [45]. In contrast, projector-based AR projects augmentation directly onto the scene, viewable to many observers at once. To retain the benefits of AR situated visualization in dynamic environments where robot operates and interacts with humans, there is a critical research gap on how to enable robots to project onto varied surfaces while moving, requiring real-time compensation that adapts to changing viewpoints, surface geometries, and lighting conditions.

In this work, we evaluate state-of-the-art deep learning-based projection compensation method, CompenHR, on a Unitree Go2 robot dog in a complex, search-and-rescue scene (Fig. 1). We contribute both quantitative and qualitative empirical evidence that identify a critical limitation: existing compensation methods are inherently static and cannot support the real-time, motion-adaptive requirements of mobile robot communication.

Specifically, our contributions are: (1) We recreate a real-world, representative search-and-rescue debris scene as an evaluation testbed with discontinuous, non-planar, strongly textured surfaces. (2) We empirically evaluate CompenHR on a mobile robot platform, combining quantitative image metrics with qualitative visual inspection across multiple viewpoints. (3) We identify a key limitation: viewpoint-specific compensation that fails to generalize as the robot moves, and we outline future research directions toward motion-adaptive and responsive projection compensation.

2 Related Work

Projectors are widely used in many applications, such as interactive entertainment [4, 5, 30, 39], immersive displays [28, 33, 41], and projector-based spatial AR [18, 34, 35, 52]. Compared to head-mounted see-through displays, projector-based spatial AR directly projects onto the environment, making situated visualizations viewable to multiple interactants or bystanders without requiring them to wear headsets or glasses. In HRI, researchers have used projectors to communicate navigation intent by overlaying a mobile robot's path with lines [10], arrows [10, 12], gradient bands [59], or simple maps [11]. Human-subjects studies show that such projections can improve comfort and perceived motion intelligence [59], lead to safer path choices [11], and increase efficiency and confidence in understanding robot navigation intent [12].

However, these systems typically assume continuously flat, weakly textured surfaces such as floors or walls. In contrast, the present work considers non-continuous, non-planar, textured construction debris as projection surfaces, where compensation becomes crucial for robust communication in realistic environments.

For immersive and accurate visual experiences on such complex surfaces, projector compensation is needed to correct geometric and photometric distortions introduced by surface shape, texture, and illumination, as reviewed in [6, 17]. For geometric correction, many methods project well-defined patterns or markers, such as structured light [15, 48], to estimate surface geometry. Others simplify this process for efficiency by designing specific patterns [29, 32, 37, 60]. Additional approaches incorporate extra sensors, such as infrared (IR) cameras [22] or depth cameras [27, 47], to track surfaces without visible patterns.

For photometric compensation, algorithms typically generate a projector input that compensates for the color and texture of the projection surface and the photometric environment. Prior work often estimates a color transfer function by projecting additional patterns [2, 7, 14]. Some recent methods jointly address both geometry and photometry, i.e., full compensation, using carefully designed patterns [40, 46].

Building on these ideas, deep learning approaches have been introduced for projector compensation. Early work focused on photometric compensation [24] and was subsequently extended to full compensation [23, 25, 26]. More recently, these methods have been further extended to high-resolution compensation, exemplified by the state-of-the-art CompenHR [57] that this work uses. For all of these techniques, however, it is unknown how they perform when deployed on a mobile robot in a realistic debris environment.

3 Method

3.1 State-of-Art Compensation: CompenHR

CompenHR [57] is a state-of-the-art deep learning method for full projector compensation that addresses both geometric and photometric distortions in an end-to-end trainable framework.

The goal of projector compensation is to find a compensated projector input image x^* such that when projected onto a textured, non-planar surface and captured by a camera, the result $\tilde{x}^*$ matches the desired appearance x': $\tilde{x}^* = \mathcal{T}(\mathcal{F}(x^*; l, s)) \approx x'$ where $\mathcal{T}$ represents geometric warping due to surface shape, $\mathcal{F}$ represents photometric transformation due to surface reflectance properties s and lighting l. CompenHR learns the inverse mapping: $x^* = \mathcal{F}^\dagger(\mathcal{T}^{-1}(x'); \mathcal{T}^{-1}(\tilde{s}))$ where $\tilde{s}$ is the captured surface image under ambient lighting.

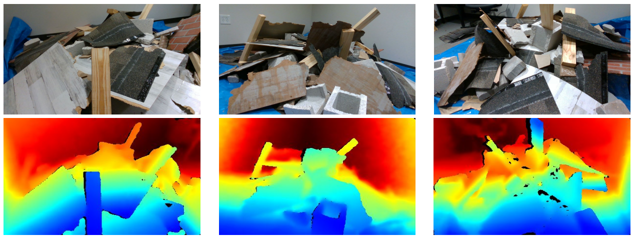
CompenHR consists of two main components: (1) *GANet* (short for Attention-based Geometry Correction Network) uses an attention-based grid refinement network to estimate a warping field that corrects geometric distortions caused by non-planar surfaces, and (2) *PANet* (short for Attention-based Photometric Compensation Network) is used to recover the high-resolution images, employing shuffle operations to correct color and brightness distortions caused by surface texture and material properties.

Potential Problem: Specifically, CompenHR learns compensation parameters for a fixed geometric relationship between the projector, camera, and projection surface. The geometric correction network (GANet) learns a displacement field that transforms the camera view to the projector's canonical frontal view. This transformation is only valid for the specific viewpoint where the training data was collected. Similarly, the photometric network (PANet) learns surface reflectance and color properties from that viewpoint. When the projector moves to a new position, both the geometric transformation and photometric properties change, but the network has no mechanism to adapt these learned parameters.

This viewpoint-specific design makes CompenHR representative of current state-of-the-art compensation methods: they achieve high quality through learning viewpoint-specific mappings, but this specialization prevents generalization to new viewpoints.

3.2 Projector-Robot System Configuration

Our projector-robot system comprises a Go2 robot dog from Unitree, Go2's camera [53], and ViewSonic LS711HD, a 4,200-lumen 1080p



(a) View from left side. (b) View from diagonal side. (c) View from front side.

Figure 2: Construction debris projection surface from three viewpoints. Top: RGB images showing complex textured surface. Bottom: Depth maps (blue = near, red = far) revealing irregular 3D geometry. The challenging surface tests compensation robustness when camera position changes.

short throw projector. This forms a similar projector–camera pair to standard ProCams setups but on a moving platform.

3.3 Recreating Search and Rescue Scene

Inspired by search-and-rescue missions in Japan, Italy, and the USA at collapsed buildings after earthquakes [9, 31, 38], we constructed a representative disaster scene (Figure 1) for the evaluation. We selected common construction materials: concrete blocks and pavers, asphalt shingles, ceramic tiles, and wooden boards. These materials exhibit diverse reflectance properties, creating realistic photometric conditions with strong textures. We broke the materials to recreate the chaotic geometry of collapse sites while maintaining real-world depth variation (Figure 2 bottom). The resulting surface presents multiple real-world challenges: (1) geometric discontinuities where materials abruptly change depth, (2) strong texture interference from wood grain and shingle patterns, (3) mixed material reflectance requiring different photometric compensation, and (4) occlusions that change depending on viewpoint.

In this real-world scene, we evaluated CompenHR to determine if existing compensation methods can support projection-based communication on a mobile robot in dynamic environments.

3.4 Evaluation Procedure

We tested four communication patterns commonly needed in search-and-rescue scenarios with human-robot teaming: a person silhouette (to indicate human detection or survivor presence), a navigation arrow (to show the robot's intended path), a plug icon (to indicate low power of the robot), and a cross symbol (to indicate blocked areas). These patterns represent typical robot-to-human visual communication needs.

For each pattern, the Go2 robot projected the image onto the debris field at three different viewpoints of the scene (Figure 2), approximately 0.5 m from the surface at 30° elevation angle:

- **View 1 (left):** Position near the left side of the debris pile.
- **View 2 (diagonal):** Position along the diagonal left side.
- **View 3 (front):** Position near the front of the debris pile.

For each viewpoint, we captured the surface image and the uncompensated projection of the pattern, as seen in Figure 3. These camera-captured images were used to generate compensated projections with CompenHR's pretrained high-resolution model.

Table 1: Average image similarity scores between compensated and uncompensated projections across four patterns, quantifying how strongly CompenHR modifies the raw projection at each viewpoint.

View	PSNR (dB) ↑	SSIM ↑	RMSE ↓
View 1 (left)	13.79	0.5171	52.14
View 2 (diagonal)	14.02	0.5558	51.39
View 3 (front)	12.71	0.5013	60.12

Then, for every viewpoint and pattern, we recorded: (1) an *uncompensated* projection (raw pattern projected directly onto the scene) and (2) a *compensated* projection (CompenHR output).

4 Results

To characterize how strongly compensation changes the projected image, we compute three standard image similarity metrics between the camera-captured compensated projection and the corresponding uncompensated projection at each viewpoint: Peak Signal-to-Noise Ratio (PSNR) [58], Structural Similarity Index Measure (SSIM) [58], and Root Mean Square Error (RMSE). PSNR summarizes the average pixel-wise intensity error; higher values indicate more similar images. SSIM ranges from 0 to 1 and captures structural similarity (1 denotes identical; values around 0.5 indicate moderate structural agreement). RMSE measures the average per-pixel intensity difference, with larger values indicating stronger deviation. Table 1 shows the aggregated results.

View-dependent photometric modification. CompenHR produces substantial photometric changes across all viewpoints when comparing compensated to uncompensated projections: PSNR values are in the low 12.7–14.0 dB range and SSIM values are around 0.50–0.56, both indicating notable differences between compensated and uncompensated projections. Views 1 and 2 exhibit similar levels of modification, whereas View 3 shows more aggressive and structurally different changes with the largest RMSE and lowest PSNR/SSIM.

Degradation in symbol structure at different views. These metrics alone do not tell whether compensation improves recognizability with respect to the ideal symbols. Fig. 3 provides qualitative insight. For several patterns, compensation improves symbol contrast or reduces background interference: For example, the arrowhead becomes more distinct at View 2, and the person silhouette becomes more uniformly colored at View 1. However, the same compensation sometimes breaks or distorts key parts of the symbols: arrow shafts become disconnected at View 3, plug prongs blur into the background at View 2, and the cross symbol's arms or legs appear truncated or bent at both View 2 and 3.

Static compensation limitation. This discrepancy between numerical similarity and visual quality demonstrates the fundamental issue: CompenHR's learned transformations are optimized for a specific projector-camera-surface configuration. When the robot moves to different views, these fixed transformations cannot adapt to the changed geometric relationships and photometric conditions, resulting in visible compensation failures.

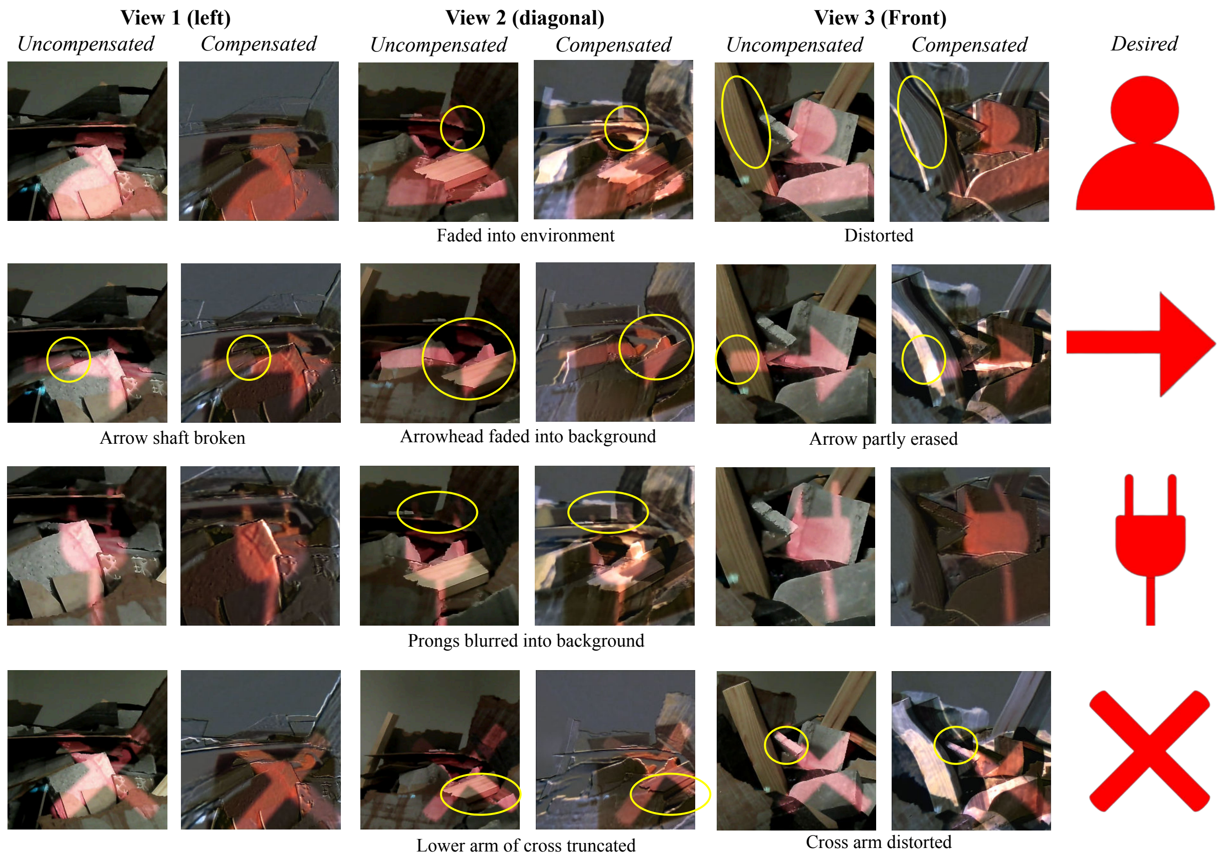


Figure 3: Projector compensation of four different patterns (person, arrow, plug, cross) on construction debris.

5 Discussion and Future Work

Our evaluation highlights both the promises and the limitations of projector compensation for projected-AR-based robot communication on complex, textured debris surfaces.

On the one hand, the quantitative and visual results suggest that CompenHR can make projected symbols more legible than raw, uncompensated projections, such as the person silhouette and the plug icon at View 1. When the robot is able to pause and project from a known, calibrated pose, static compensation may be sufficient to support simple symbolic communication, such as indicating directions or marking human detections.

On the other hand, the degradation observed at certain viewpoints (notably View 3), where RMSE increases and structural artifacts appear in Fig. 3, reveals a mismatch between current compensation algorithms and the realities of mobile robots. Methods like CompenHR are static: they assume a fixed geometric relationship between projector, camera, and surface, and they learn viewpoint-specific mappings. A mobile robot, however, must communicate while navigating, turning, and repositioning with respect to both humans and the environment. Under these conditions, a one-time calibration and fixed compensation field are not enough. Moreover, image-based metrics such as PSNR, SSIM, and RMSE do not fully capture human-centered outcomes that matter in HRI, such as whether humans can reliably interpret the symbol and how quickly they can recognize it.

Inspired by those needs, we lay out several future directions:

1. Geometric Adaptation with Continuous Tracking. Rather than learning fixed warping fields with a static-world assumption, future methods could track surface geometry continuously using visual markers or SLAM. As the robot moves, the compensation module would retain most of its warping and update it partially based on the new additions of the view, narrowing down the search space while still allowing projections to remain spatially aligned with the environment.

2. Low-latency Photometric Compensation. The CompenHR architecture is computationally heavy and not designed for real-time inference. Future work can explore lightweight photometric models, probably trade some accuracy for significantly reduced latency, targeting update rates compatible with a robot's movement.

3. Human Evaluation. Finally, user studies are needed to measure how compensation quality and update rate affect human interpretation of compensated projections, task performance, and trust. Combining objective image metrics with behavioral and subjective measures will help determine what level of compensation is good for different HRI scenarios and guide algorithm design toward human-relevant performance.

6 Conclusion

On a mobile robot in a search-and-rescue debris environment, we evaluated state-of-the-art projector-compensation method, CompenHR. Our results show that compensation can improve the recognizability of projected symbols on textured, non-planar surfaces at a calibrated pose, but degrades as the robot moves to new viewpoints. This gap between static compensation and dynamic, real-time communication needs in mobile HRI motivates future work on motion-adaptive, human-centered projection methods.

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