

Enhancing the Accessibility and Robustness of Above-Neck Gesture Interfaces in Immersive Environments Using Adversarial Images^{*}

Siyu Zhang¹, Yelu Gu¹, Wenda Zhao¹, Kirsten Cater¹ and Oussama Metatla¹

¹University of Bristol, Bristol, United Kingdom

Abstract

As XR headsets with built-in cameras become more common, above-neck gestures, especially facial gesture controls, are now widely used in immersive environments. However, people with motor impairments often find it difficult to precisely control these gestures, which limits their ability to utilize such interfaces. To address this issue, we propose a gesture deviation correction method based on adversarial attacks to enhance the recognition of intended gestures, thereby enabling this user group to interact more effectively with gesture interfaces.

Keywords

XR, Adversarial attacks, Adversarial image techniques, Facial recognition, Motor impairment

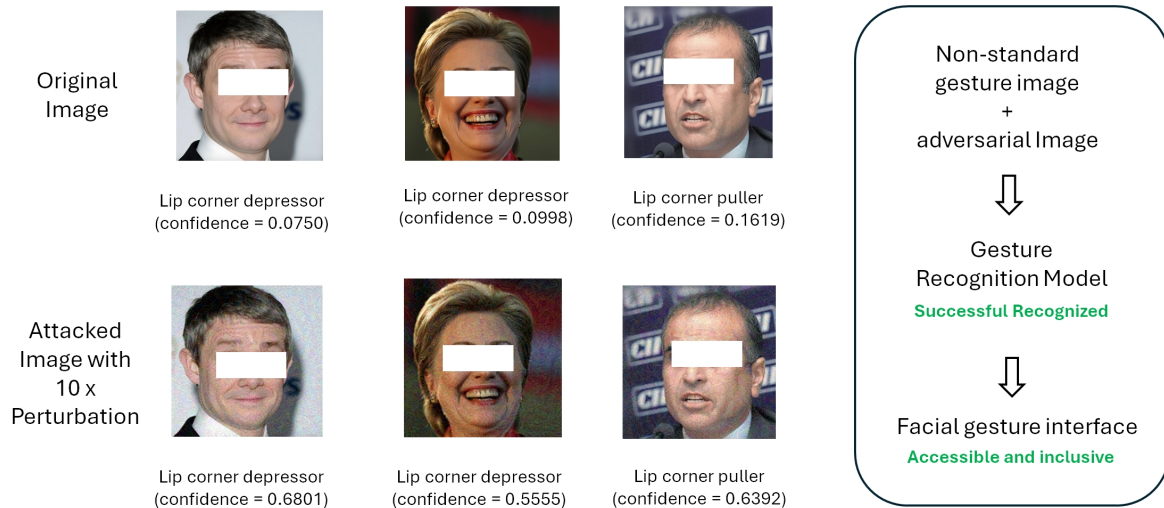


Figure 1: Illustrative diagram of using adversarial noise to alter image classification results and the concept of applying this technique to enhance the recognition of non-standard gesture images in individuals with motor impairments. (Since the perturbations are extremely subtle and imperceptible to the human eye, the perturbation is scaled up 10× for visualisation.)

1. Introduction

With the increasing prevalence of built-in cameras in extended reality (XR) head-mounted displays (HMDs), above-neck gesture interface, including facial gesture interfaces have emerged as a cost-

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^{*}Corresponding author.

[†]These authors contributed equally.

✉ s.zhang@bristol.ac.uk (S. Zhang); yelu.gu@bristol.ac.uk (Y. Gu); ed20979@bristol.ac.uk (W. Zhao); kirsten.cater@bristol.ac.uk (K. Cater); o.metatla@bristol.ac.uk (O. Metatla)



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effective solution for enabling device access for users who are unable to operate traditional hand controllers, such as individuals with limb deficiencies or motor impairments[1, 2]. These interfaces have been widely integrated into augmented reality (AR), virtual reality (VR), and mixed reality (MR) systems [3, 4, 5], offering intuitive and efficient interaction methods for both system control and gaming applications. However, recent studies[6, 7] highlight that certain user groups, including individuals with proprioceptive impairments, muscular weakness, or neurogenic motor disorders, often encounter challenges in achieving a satisfactory user experience with these interfaces. Due to difficulties in precisely controlling their facial movements, these users frequently struggle to execute their intended gestures accurately. As a result, the input data may significantly deviate from standard gesture patterns, leading to recognition algorithms failing to interpret the user's intended gestures correctly. This limitation underscores the need for innovative approaches to enhance the accessibility and usability of gesture interfaces for individuals with diverse physical abilities.

Traditional approaches to addressing this issue involve providing customized interfaces[1] for this user group or training personalized recognition models[8, 9, 10]. However, these methods come with significant drawbacks: the former may negatively impact user experience[1], while the latter is often costly and computationally intensive[10]. To address these challenges, this study proposes a novel approach aimed at reducing the disparity between inaccurately performed gestures and their corresponding standard-intended gestures within the recognition model framework. The underlying hypothesis of this research is that although individuals with disabilities may execute gestures inaccurately, these gestures remain closely aligned with their intended and standardized forms. To operationalize this assumption, the study introduces a method that utilizes adversarial attack techniques, such as Fast Gradient Sign Method (FGSM) [11] and Projected Gradient Descent (PGD) [12], to generate controlled perturbations in facial gesture data. These perturbations are designed to compensate for users' motion inaccuracies, thereby enabling the recognition algorithm to produce outputs that more accurately reflect the user's intended gestures. This approach has the potential to enhance accessibility in facial gesture-based interactions within virtual reality (VR) environments. A significant advantage of this method is that it eliminates the necessity of retraining the recognition model, thereby substantially reducing computational resource requirements. Furthermore, the proposed technique does not increase the complexity of the recognition model, mitigating the risk of overfitting and ensuring robust performance. This innovative approach represents a promising advancement in facilitating more inclusive and efficient gesture-based interactions for users with disabilities in VR applications.

In our preliminary attempts, we have confirmed that adversarial attack techniques can effectively alter facial gesture classification results. In further experiments, we will investigate the effectiveness of adversarial images in enhancing facial gesture recognition for individuals with motor impairments. Positive outcomes would motivate further research on leveraging this technique to improve the accessibility of facial gesture interfaces. Potential applications include developing a gesture deviation correction system based on adversarial images or designing wearable devices with physically perturbed visual patterns to aid users in producing more recognizable facial gestures.

2. Related Work

2.1. Inclusive Above-neck Gesture Interface

Above-neck gesture interfaces for individuals with motor impairments have been a significant focus in past research. Zhao et al. [1] proposed allowing users to create their own gestures, but they found that individuals with motor impairments often abandon complex gestures due to their physical conditions. While this method accommodates users' abilities, it does not resolve the conflict between personal capabilities and intended gestures. For example, in recent studies [13, 14, 15], users tended to associate the smile gesture (upward movement of the mouth corners) with the "confirm" command because they perceived the semantic features of the gesture to align with those of the command [13]. However, due to differences in motor abilities, the user with motor impairments cannot perform facial gestures accurately [7], leading them to abandon their preferred gestures in favor of alternative ones, which can

significantly impact their user experience.

To address this challenge, recent gesture algorithm research has started to consider inclusivity [8]. Although recent studies have suggested that recognition algorithms should account for the diversity of user abilities during training [16], significant disparities in facial gesture abilities between non-impaired and severely impaired individuals can lead to increased model complexity, ultimately causing overfitting, which severely impacts recognition accuracy [17].

In recent studies [8, 9, 10], researchers have developed gesture recognition models specifically trained for individuals with motor impairments, achieving good recognition results. However, since the motor abilities of individuals with motor impairments are highly diverse, training personalized models for each individual would result in prohibitively high development costs, especially for existing mature AR, VR, or MR facial gesture interfaces (e.g., [3, 4, 5]), where redeployment costs would be significant.

2.2. Adversarial Attacks and Recognition Optimization

Adversarial attacks refer to the application of imperceptible perturbations to human eyes but can cause deep learning models to misclassify inputs [11]. Adversarial examples are primarily used to manipulate model predictions and are often regarded as malicious attacks [17]. However, in recent years, researchers have begun to exploit adversarial attacks for beneficial purposes, a concept referred to as benign adversarial attacks [18], with applications such as optimizing Turing tests [18] and privacy protection [19].

Notably, adversarial examples have recently been leveraged to improve image recognition performance. Salman et al. employed adversarial attacks to enhance the recognition of vehicles under extreme weather conditions [20]. The adversarial attack model learned the features of vehicles under normal weather conditions and embedded these features as perturbations into images captured in extreme weather, thereby improving recognition accuracy. This approach boosts neural networks' ability to classify objects with high confidence, significantly enhancing system performance and robustness—even in the presence of unforeseen data shifts or corruption [20].

3. Proposal

Building upon the demonstrated superiority of adversarial imaging techniques in optimizing image recognition for distribution-shifted and corrupted datasets, we propose adapting this approach to facial gesture recognition for those with motor impairments. The primary challenge in facial gesture interfaces for this population stems from persistent deviations between user-executed gestures and standardized gesture templates. Our previous interviews, which focused on individuals with motor impairments, uncovered challenges in facial gesture execution that critically impact interface usability. Participants with muscular weakness demonstrated incomplete facial expressions - for example, attempting a smile might result in partial lip stretching rather than full facial engagement, causing emotion recognition systems to miss intended inputs. Meanwhile, users with coordination-related motor disabilities exhibited directional control limitations, such as being unable to maintain precise eye gaze patterns required for face authentication in mobile applications. These discrepancies between users' physiological capabilities and system-recognized gesture patterns are quite common in this demographic, suggesting fundamental incompatibilities in current facial interface design.

Adversarial image techniques are particularly well-suited for addressing recognition challenges caused by data shifts[20] (i.e., inaccuracies in gesture execution). In our preliminary attempts, we employed one of the most commonly used adversarial attack methods—PGD attack[12]. By adding perturbations to less standardized facial gesture images, such as the gesture image of a stretched mouth corner shown in Figure 1, we were able to alter the classification result from a widely used facial action unit model[21]. For example, after the perturbations were added, the first image was successfully recognized as a mouth lip corner depressor (confidence = 0.6801), a classification that was not achievable without the perturbations (confidence = 0.0750). These positive results confirm that adversarial attacks

can effectively modify the classification outcomes of facial gesture recognition models, making them more adaptable to gesture variations caused by motor impairments.

The gesture deviations in individuals with motor impairments are highly diverse. In our subsequent experiments, we will apply various types of adversarial attacks to test their effectiveness in optimizing the recognition of different gestures within this user group. If adversarial images are proven to effectively enhance the recognition accuracy and robustness of facial gestures for individuals with motor impairments, we will explore how to incorporate this technology into facial gesture interfaces in a cost-effective manner to improve accessibility for this population.

For users who face difficulties with recognizing a single gesture, physical adversarial attacks may offer a low-cost and convenient assistive solution[22]. Users can wear facial accessories, such as glasses or painted designs, that contain specific perturbation patterns, enabling continuous optimization of the recognition of a particular gesture. However, a limitation of this approach is the restricted input angles for the images[22]. When these perturbation patterns can be made dynamic, for example, using wearable display devices such as integrated display on glasses[23], or on-skin displays like wearable electronic tattoos with moving perturbation designs—the angle restrictions can be minimized, and the range of gestures that can be optimized expands. The downside, however, is that displays integrated in glasses may not provide sufficient display areas, while on-skin electronic tattoos are still at the early stage of development and currently relatively expensive[24]. In contrast to physical attacks, adversarial image attacks are characterized by their stealth, adaptability, and low cost[25]. We can directly add perturbations to each frame of the image captured by the camera and then pass the perturbed image to the recognition model, enabling real-time optimization of the recognition results. This is the attack method we are currently investigating.

4. Future Work

When adversarial techniques are appropriately applied, they transcend their conventional perception as "attacks" and instead emerge as a transformative tool for enhancing accessibility to emerging technologies for individuals with diverse abilities. For example, the strategic introduction of image perturbations could enable individuals with eye movement disorders to utilize facial recognition systems, such as Face ID, through camera-based interfaces. Similarly, perturbations could be applied to facilitate the recognition of finger gestures for individuals with partial finger amputations, thereby granting them access to hand gesture-based interaction systems. Furthermore, adversarial perturbations could be employed to modify the recognition of movement amplitude, allowing individuals with motor impairments to engage in pose gesture games by ensuring that subtle movements are interpreted as larger, intentional gestures.

Currently, the reliance on built-in cameras and gesture interface devices has inadvertently excluded individuals with motor impairments from participating in the metaverse. However, adversarial techniques hold significant potential to serve as a gateway, providing these individuals with equitable and barrier-free access to the immersive environments of the metaverse. By leveraging these methods, it becomes possible to create inclusive digital spaces that accommodate a broader spectrum of physical abilities, thereby fostering greater accessibility and participation in the evolving landscape of virtual worlds.

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Declaration on Generative AI

During the preparation of this work, the author(s) used ChatGPT in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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