Human-Machine Interfaces Using Augmented Reality

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ABSTRACT

In recent decades, infrastructure aging, new social behavior, urban and rural environmental changes, and nature extreme events have increased in complexity. When disasters occur, saving lives, and providing access to emergency teams is a priority where every second saved is critical. Researchers in Structural Health Monitoring (SHM), government laboratories, and industry leaders are using sensors, field deployments, algorithms, and signal processing to assist and prioritize decisions. If the collection of data would be accelerated with near-real time interface with engineers in the field, emergency responders, safety, and maintenance could be integrated with machines in real-time, and new solutions could be advanced. This paper summarizes new work on human decisions exploring the concept of human-machine-structure interfaces associated with structural dynamics and damage, to transform human decisions using new interfaces. The interface between human and structures is achieved with Augmented Reality (AR). The results include work in human-in-the-loop with application on near real-time computer vision, human-robot teaming, and a new infrastructure maintenance paradigm centered in augmenting the capabilities of humans in the field. The platform of human-robot teaming is further advanced in dynamics and control of humans using data obtained from robots and vice versa. Future research includes human-centered inspections, and human-machine control theory.

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INTRODUCTION

The increasing complexity of infrastructure, evolving social behavior, environmental changes, and natural disasters necessitate effective decision-making and timely response. Researchers, government laboratories, and industry leaders are leveraging sensors, algorithms, and signal processing for improved decision-making and safety integration. However, there is a need for accelerated data collection and real-time communication. This paper explores the use of AR as a human-machine-structure interface to enhance decision-making processes. AR provides real-time, three-dimensional visualization, overlaying computer-generated content onto the physical environment, thereby improving the user experience and decision-making capabilities.

This paper explores the applications of AR technology in structural dynamics and damage, focusing on human-centered crack inspections and human-robot interaction (HRI). Traditional image-based crack inspection methods have limitations in real-time processing and compatibility with human inspections. By integrating AR into crack detection, the process can be transformed with real-time data acquisition, hands-free detection, and overlaying crack indications on the real structure. The paper presents a human-in-the-loop computer vision methodology that utilizes AR head-mounted display devices to enhance the accuracy, comfort, and efficiency of crack inspections.

The paper also explores AI-driven HRI methodologies, including the use of sensors and the benefits of combining AI algorithms with AR technology. AR-driven HRI leverages the immersive nature of AR to create interactive environments for humans to interact with robots, enhancing perception and enabling safer inspections of infrastructure. The paper proposes an AR interface architecture that combines real-time data analysis by robots with human control and computer-generated information through AR, facilitating effective planning and task prioritization.

AR TO INTERFACE HUMAN, MACHINE AND STRUCTURE

AR Overview

AR refers to the superimposition of digital or computer-generated content onto the physical environment. It merges virtual and physical components in real-time and three dimensions. Unlike virtual reality (VR), where users are fully immersed in a virtual environment, AR enhances the user's experience of the physical environment by providing a visualization of virtual objects within the real world. Initial attempts to incorporate AR into engineering applications started in the 1960s. However, early holographic optical elements had limitations in terms of resolution, mobility, and field of view, which limited their practicality. In the following decades, the research community focused on addressing visualization and technical challenges. Since the 2000s, AR technologies have advanced significantly, enabling the development of prototype solutions for engineering. The institutionalization of AR technology in engineering applications depends on future progress in AR software and hardware.

This includes reducing device weights, improving processing capabilities, resolving compatibility issues, and enhancing holographic lenses and field of view for AR head-mounted devices [1].

AR Applications in Structural Inspection

AR has shown potential for infrastructure inspection and vibration analysis. By simulating designed structures before construction, providing virtual site visits, and facilitating online interaction, AR enhances the inspection process. Additionally, AR enables a more comprehensive and accurate assessment of infrastructure, improving decision-making and maintenance strategies [2], [3]. Through the time machine measuring application, users can save and restore virtual representations of physical objects, allowing them to measure and track changes based on color-coded representations. This capability is particularly relevant for SHM, as inspectors can detect damage patterns and assess the progression of structural changes over time [4]. AR empowers inspectors to gain deeper insights into the behavior of structures and make informed decisions based on real-time data [5].
AR has capabilities in automation and control of robots for infrastructure management. By integrating AR into robot control interfaces, users can view the environment from the robot's perspective and execute commands for sensor pick-and-place sequences. This technology proves especially beneficial in hard-to-access areas where traditional construction methods are costly and time-consuming. Robots equipped with AR capabilities can inspect infrastructure in hazardous or challenging locations, enhancing safety and efficiency. The integration of AR and robotics holds tremendous potential for optimizing the construction and maintenance of infrastructure [6].

INTERFACES FOR AUGMENTING HUMAN CAPABILITIES

This section describes the interfaces used for augmenting the capability of humans in this research.

Human-Centered Crack Inspections

Past studies have proposed novel image-based crack detection with high accuracy and near real time processing capabilities. However, image-processing crack detection depends on use of computer, and a human user needs to orient the real crack based on the crack image on computer screen. Because crack positioning from an image is a time-consuming process and therefore even if the computer is in the field, the processing is not in real time. Therefore, the proposed image-based crack detection methods are not compatible with human field inspections. To adjust image-based crack detection for human inspectors, past studies proposed using AR platform. This approach can be implemented by deployment of an image–processing crack detection/characterization tool in AR head mounted display (HMD) devices that transforms human visual inspection process through real-time acquisition and processing of field data. This section shows the transformation of the image-based crack detection/characterization methodologies to AR domain.

HUMAN-IN-THE-LOOP COMPUTER VISION METHODOLOGY

This research employs HoloLens headset by Microsoft Corporation to implement the methodology (Figure 1) but the methodology is applicable for any AR-HMD devices with integrated computing capability. Csharp programming language and Unity Game Software were employed to process the pattern recognition algorithm. First, a median filter reduces the noise in the image and then Canny algorithm with Sobel Kernel extracts the crack. Afterwards, the pixel counts between the crack edges are evaluated and the width and the length of crack in pixel is estimated. Then the research team employs the capabilities of AR-HMD devices to determine the headset-crack distance and thereby change the crack pixel count to metric or imperial measurement. Finally, the AR-HMD devices overlay the crack with a crack image in a noticeable color and show the measurement in front of the user [2].

EXPERIMENTS AND RESULTS

Figure 2 shows the AR-HMD devices overlay the crack with crack image in a noticeable color and Figure 3 shows the measurement in front of the user.

Figure 1: the AR-HMD device to implement the methodology.

(a) (b)

Figure 2: crack detection with AR-HMD devices; (a) unprocessed image (b) processed image inside the AR-HMD device

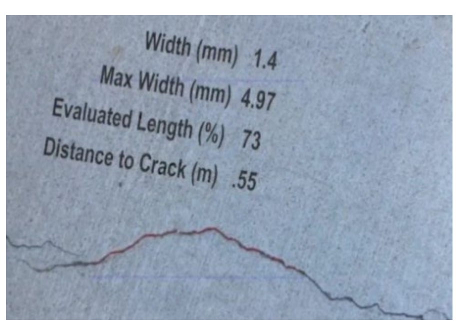

Figure 3: crack measurement with AR-HMD devices

In addition, the research group conducted several detection and measurement experiments. The results of crack detection field-test confirm the practical effectiveness of the developed AR application. For instance, the results show that the AR tool detected 75% of the length of tested cracks during the experiments, and the maximum error for the measurement of the crack width in field and laboratory experiments are 16.7% and 13.3%, respectively.

HRI APPROACH

Despite significant progress in robotics technology, HRI remains a significant challenge [7]. Past studies has highlighted the significance of this interaction in different fields of application, for example, according to research presented in [8], approximately 90% of small-to-medium-scale enterprises in the United States could benefit from collaborative automation.

In the context of human-centered automation, whose principles are outlined in [9], the primary focus of HRI is on prioritizing human safety, optimizing ergonomics, and enhancing the collaborative efficiency of work processes. Additionally, robots need to communicate and interact with humans in a natural and intuitive way meaning that robots must be able to recognize and interpret human behavior, and communication patterns and respond appropriately. The rest of this section explores different strategies for human robot teaming using AR and AI and proposes a method to integrate AI and AR for HRI.

AI-DRIVEN HRI

Methodologies using AI-based HRI conventionally have two main steps. In the first step, an AI algorithm based on the data acquired by a sensing system infers human-action intention. In the second step, a robot-control policy based on human-action intention step is constructed and implemented. The sensing systems are broadly grouped under one of the wearable and nonwearable sensors. TABLE I shows the attributes that are usually measured in wearable and nonwearable sensors and some exemplary publications that have gathered those cues. Additionally, red-green-blue (RGB) cameras are commonly used as imaging sensors in non-wearable sensing systems.

There are three primary approaches to estimate human intention: intention parameter estimation, action recognition and intention classification, and inverse optimal control/inverse reinforcement learning (IRL)-based intention inference. Intention parameter estimation involves modeling continuous or discrete dynamics using dynamic neural networks (NNs) with noise for deterministic modeling [15]. In the case of probabilistic models, Gaussian processes (GPs) and Gaussian mixture models (GMMs) are used [16]. Humans can also be represented by their motion dynamics for estimating the class of human intention using hidden Markov models (HMMs) [17], dynamic Bayesian networks [18], and conditional random fields (CRFs) [19]. The third approach involves representing action plans as policies in terms of state-action pairs. Then to model intention-driven behavior, inverse optimal control (IOC) [20], and inverse reinforcement learning (RL) algorithms are employed, where the intended motion maximizes an unknown objective or reward function [21]. In the context of infrastructure inspection and maintenance, AI-driven HRI can transform the way we carry out these critical tasks. By using AI algorithms, robots can interpret and analyze data collected by sensors to identify potential issues and prioritize them for human attention.

AR-DRIVEN HRI

There are three commonly used strategies for HRI using AR, namely the control feedback, workspace, and informative approaches [22]. The control feedback approach primarily utilizes AR elements to provide feedback on user-generated paths or generic inputs. Path feedback involves providing information on a series of interconnected points created by the user, while input recognition focuses on offering feedback on various user inputs. The workspace approach involves utilizing AR content to display the occupied area by the robot manipulator. The primary goal is to ensure a safe working environment by highlighting potential collision zones with the robot. On the other hand, the informative approach utilizes AR technologies to visually present general information related to either the industrial robot or the specific task at hand.

Figure 4 shows the architecture of the AR interface used for HRI in this study. The interface is tested using a Microsoft HoloLens AR-HMD and a Kinova Gen3 robotic arm. First humans can intuitively change the position of the holographic gripper and constraints for intuitive robot control (step 1). Next, the transformation of the mentioned holograms including their rotation and position are achieved using the headset capabilities (step 2). The transformation matrix between the robot base frame and AR headset coordinate systems were previously experimentally calculated using a calibration setups (step 3). The headset and base frame coordinate systems are shown in Figure 4. The position and orientation of the holographic objects are reported to a computer modeling software that is Matlab where the safe trajectory is planned for the real robot (step 4). Humans can see and confirm the robot's planned path both on the computer and in AR-HMD using their own discretion (step 5). If the path is confirmed by humans, the joint angle for the trajectory is computed based on inverse kinematic of the Gen3 arm model (step 6). Finally, a high-level command is sent to the Matlab Application Programming Interface (API) for Kinova Gen3 to move the robot arm using its forward kinematics functionality (step 7).

CONCLUSION

The integration of AR technology into human-machine interfaces has the potential to revolutionize decision-making processes in engineering applications. This article has highlighted the advancements in AR technology and its applications in structural dynamics, damage detection, and infrastructure inspections.

It has also explored the potential of HRI and the integration of AI algorithms to enhance the collaborative efficiency of work processes. Future research in human-centered inspections and human-machine control theory will further advance the capabilities of AR in engineering applications.

TABLE I. STUDIES THAT MEASURED THE CUES WITH WEARABLE AND NONWEARABLE SENSORS

Publication	Measure cues	Type
[10]	Heart Rate	Wearable
[11]	Skin Response	
[12]	Electromyography	
[13]	Human Emotion	Nonwearable
[10]	Approval Responses	
[14]	Skeletal Movement	

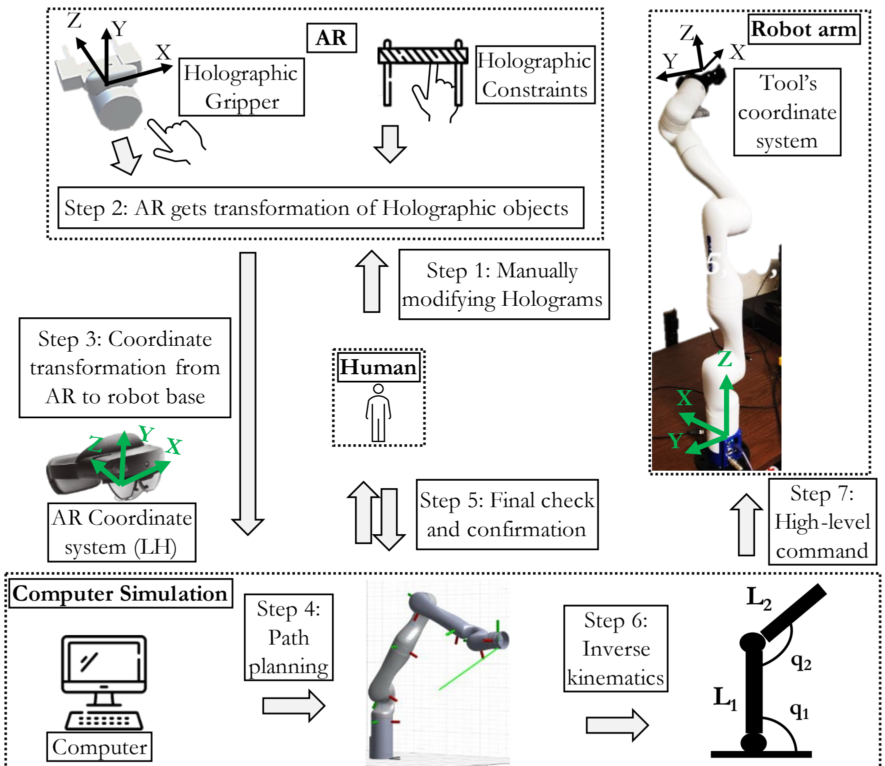

Figure 4. the architecture proposed AR interface for HRI

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