Review on Human Computer Interaction Intelligent Learning for Improved Identification Procedure

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Abstract

Every day, new systems and devices are being developed, and research in this human and computer interaction field has increased dramatically over the previous several decades. Research into how computers impact people's lives, organizations, and society as a whole is done via the field of Human-Computer Interaction (HCI). This involves not just the simplicity of use but also innovative interaction approaches for supporting user activities, offering better access to information through new HCI principle, and establishing more powerful forms of communication for the user. After contemplating its potential, HCI is currently a popular new study topic among academics with feedback and recommendation by yes or no. To make HCI an effective tool, it must learn from the new principles of HCI that is planned here for future and reconsider some of its fundamental concepts.

Keywords: Human-computer interaction, machine learning, data augmentation, autonomous vehicle, human activity recognition

1. Introduction

Interfacing has always been an issue when using computers. Human-computer interaction has gone a long way in the past days. The HCI has seen a number of changes throughout the years, apart from the quality of interaction. It is the goal of HCI research to develop human-centered capabilities so that designers may use these concepts and approaches to build intuitive user interfaces for any device as shown in figure 1. Computers now play a vital role in healthcare and education. Notebooks, tablet PCs and smartphones have become nearly universally available in today's society. Since electronic devices may give more realistic facilities, they are becoming more important in healthcare and educational settings. It is also hoped that pupils would benefit from utilizing digital gadgets in the

classroom because of this. Digital gadgets are clearly a positive influence on student achievement, motivation, and capacity to apply what they learn in class [1-5]. Figure 1 shows the dataset for Human activity perception.

There are several ways in which the Human Activity Recognition (HAR) approach has enhanced the everyday lives of people. Installing sensors at the prescribed places is an essential part of any data-driven HAR system, regardless of what sort of HAR system is being used. A position-specific dataset was used to train the ML classifier.

Figure 1. Human activity recognition [28]

To utilize the HAR system, a user must wear a wristwatch or smartphone or be active in a certain region to activate a sensor, which has been steadily integrated into everyday devices such as cell phones. It allows the user to avoid making a hasty decision on where to set the sensor because of the system's built-in positioning [6,7]. However, not all users can benefit from equipment in a permanent posture. There may also be a variety of physical conditions and preferences when it comes to the wearable sensors. The sensor region is important to predict the motion estimation very effectively.
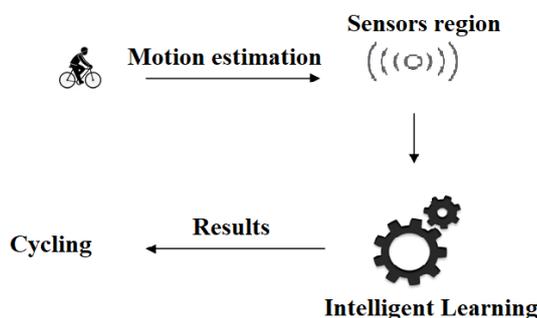

Figure 2. Human Activity Recognition with sensor

Sensors may be installed to limit the detecting area of non-wearable devices. In general, HAR systems' interior design takes a wide variety of sensor placement options into account. For HAR systems to work well, designers must be familiar with the most incredible

precision of sensor placements and numbers. So, from the perspective of human-computer interaction intelligent, it is appropriate for both HAR developers and individuals who use them to provide a strategy to help make judgments regarding sensor location in a particular context [8-11]. Reflecting on the current state of affairs, this paper proposes a new way of thinking about our connection with technology. Human values need to take centre stage in a more comprehensive collection of lenses, tools, and procedures. There are both good and bad parts to this; people utilize technology to live healthier and more happy lives, but they also use it to enhance their creative abilities with digital tools and obtain fast access to knowledge that was previously inaccessible. While governments increasingly depend on computers to maintain social order, criminals are becoming more sophisticated as a result of technological advancements, and citizens are becoming more concerned about how their personal information is being maintained [12, 13].

2.   Related Works

2.1 Virtual Data Augmentation

The Virtual Data Augmentation (VDA) is used to increase the number of persons in the dataset in order to better identify data collected in the actual world. Besides, the VDA is used to measure the sensor data from the wearable format sensor with the intermediate dataset, according to the sensor output. It is expected that the sampled data will be represented in terms of either time- or frequency-based in the magnitude domain. So the VDA techniques used are based on the time and amount of data that is being gathered. It has worked out as described:

2.1.1 Permutation

Changing the time position of the supplied data is a kind of permutation. The data are randomly shuffled about in a single data window after being divided up into many pieces.

2.1.2 Time warping

Temporal locations may be distorted in the process of time warping. Previously, the original window's separated sections were rearranged by time location.

2.1.3 Magnitude warping

Warping the signal's magnitude is known as "magnitude warping". A smooth curve increasing in radius around one is used to confound the magnitude of the data.

2.2 Positioning of HAR and Related Sensors

According to diverse applications using various devices, each HAR system has benefits to consider. The most informative input source is a camera; therefore, it gets a lot of focus. It has also been frequently employed in conjunction with a non-vision-based system that is connected to a person's body. It is used as an improved represent of the variance in the body structure movement. Infrared sensors, distance sensors, pressure sensors, EEG signals, ambient light, and so on can all be used for motion recognition in a variety of ways, such as detecting temperature changes [13] and so on.

The first comprehensive investigation of where a computer mouse's sensor should be placed was carried out by Kim et al. [14]. The impact of sensor placement on the body structure movement display has been researched extensively in various domains. A study by Kunze et al., [15] examined the locations placement put on the human body structure and offered a way to minimize the impact of varied locations on wearable accelerometers. There have been a number of studies that have examined sensors worn on the body in a variety of ways [16]. However, their research only revealed a general trend in accuracy over a wide range of tasks and numbers, rather than identifying specific locations where activity identification would be most effective. As a result, it has become increasingly a commonplace in building/structure health monitoring. There are a number of places where the sensor may be put, such as the living room [17, 18].

2.3 Voice control input

With voice input, there are many applications such as the one remotely providing input through microphone or any other devices that may be supported, overcoming the disadvantages of touch or hand motion inputs. This voice input has been adopted to assist or guide the driver in autonomous vehicle operation. When using hands-free technology, autonomous driving car drivers use voice input control through microphone, because they don't have to move their hands. If you're in a loud environment, such as in a room full of people, you may not be able to use your voice to control your vehicle. The non-AV research proposes multimodal voice inputs, such as speech with touch or hand gestures, to make voice input instructions more intuitive [19]. For the sake of time, participants favour speech + touch to voice + hand gestures, despite the former being more natural, intuitive, and less cognitively taxing. Voting alone has been demonstrated to take longer than using voice and eye contact to answer a question.

3. Various Applications

3.1 Fully Autonomous Vehicle

The main responsibility of the driver is the best vision-based operation due to increased vehicle autonomy, which is mostly driven by AI development [20]. Altering one's posture within the Fully Autonomous Vehicle may accompany this shift in activity (FAV). Reclining the seat, for example, places the driver further away from the dashboard than when driving normally [21]. Although the physical and cognitive capabilities of drivers vary amongst NDRTs, this variation is impacted by the differing manoeuvre and non-manoeuvre intervention situations. Traditional speech and touch interface is very suitable, and to handle the dynamic operation through cognitive approach, drivers are not sufficiently supported to carry out various intervention scenarios.

3.2 Personas and Methods

It is essential that the whole interactive software development process [22] include usability as a quality criterion [23]. Users must be taken into consideration while developing an useful software system [24]. The Personas is one of the strategies with the HCI for doing user analysis, essentially researching and modeling the person who will use the software system. Users' preferences are taken into account in the design of the program, rather than the developers' preconceptions, in order to avoid creating a plan based on their own assumptions. The word "personas" is capitalized while discussing the approach, and the lowercase "persona" is used to describe a single user type.

With the Personas methodology introduced by Alan Cooper, designers may better understand the behavior of actual users by creating user models based on their observations. A person may be fictional, but its aspirations are based on what users have informed, thus they are genuine.

3.3 Identifying Human Interaction

To utilize the HAR system, a user must wear a wristwatch or smartphone or be active in a certain region to activate a sensor, which has been steadily integrated into everyday devices such as cell phones. Users don't have to make arbitrary decisions about where to place sensors in HAR because of the system's design [25].

However, not all users can benefit from equipment in a permanent posture. It's possible that the wearable sensor type's subject will have varied physical conditions and

preferences. Sensors may be installed to limit the detecting area of non-wearable devices. In general, HAR systems' interior design takes a wide variety of sensor placement options into account. Selecting a sensor location that is convenient for both the design and the system's performance is a delicate balancing act that must be taken into consideration. For HAR systems to work well, designers must be familiar with the most incredible precision of sensor placements and numbers. So, from the perspective of HCI, it is appropriate for both HAR developers and individuals who use them to provide a strategy to help make judgments regarding sensor location in a particular context [26].
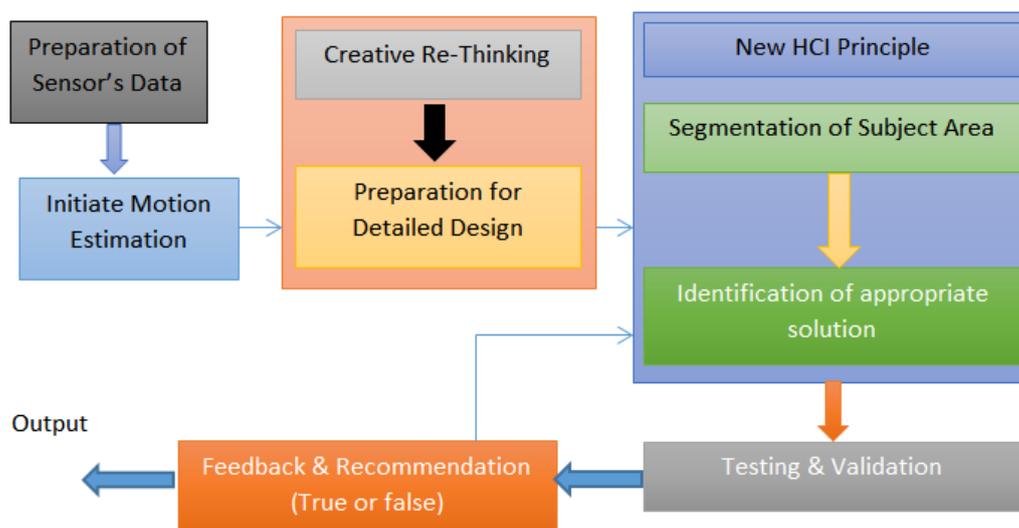

Figure 3. Feedback recommendations with new HCI principle

3.4 Collaboration on Terrain Sketches

A paradigm shift in how humans connect with information and each other has occurred thanks to mobile devices, which have enabled the workplace to be turned into a highly interactive environment [27]. However, this expansion of access to technology comes with a slew of drawbacks. When it comes to complicated systems, such as 3D modeling software, professionals and those with extensive expertise are often the ones who utilize them. This makes it more difficult for individuals with diverse degrees of expertise to participate in addressing a complicated issue, hence it is vital to make these systems simpler to grasp.

People's daily interactions should be made easier as well. It is possible to find a wide range of 3D modeling tools in HCI model creation software sector; within this tool, there is a high learning curve for novices. The user interface is often complicated and the interaction can be difficult. Since most people aren't familiar with these cameras, it might be difficult for

them to move the camera in the direction they want it to go. As a result, novice users may not be able to easily identify the structured body motion model in 3D from image view that can prove in the motion estimated software.

4. Conclusion

By focusing entirely on the potential benefits that new skills and technologies will offer, it's simple to feel enthused about the future. It's important to maintain a healthy amount of equilibrium, of course. HCI, in particular, has to take into account the global aspect of the future. Computer systems are being used all across the globe in equally fascinating ways as new innovative technologies arise. There are several models and methodologies that may be used in interdisciplinary and transdisciplinary research. Different research methodologies, tools, and data kinds must be integrated into a single framework. Another vital qualification is willingness to discourse and receptivity to new views, viewpoints, and methodologies from various disciplines and fields of study.

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