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WRITING WITH WIFI SIGNALS FOR VIRTUAL REALITY DEVICES

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Abstract: **In this paper recently, handwriting recognition approaches has been widely applied to HCI (Human-Computer Interface) applications. The emergence of the novel mobile terminals urges a more man-machine friendly interface mode. The previous airwriting recognition approaches have been accomplished by virtue of cameras and sensors. However, the vision based approaches are susceptible to the light condition and sensor based methods have disadvantages in deployment and high cost. The latest researches have demonstrated that the pervasive wireless signals can be used to identify different gestures. In this paper, we attempt to utilize CSI (channel state information) derived from wireless signals to release the device-free air-write recognition called WriFi. Compared to the gesture recognition, the increased diversity and complexity of characters of the alphabet makes it challenging. The PCA (Principle Component Analysis) is used for diagnosing effectively and the energy indicator derived from the FFT (Fast Fourier Transform) is to detect action continuously. The unique CSI waveform caused by unique writing patterns of 26 letters serves as feature space. Finally, the HMM (Hidden Markov model) is used for character modeling and classification. We conduct experiments in our laboratory and get the average accuracy of the Wri-Fi are 86.75% and 88.74% in two writing areas, respectively.**

Keywords: Augmented Reality, Virtual Reality

I INTRODUCTION

In this work, aim to design a device-free air-writing recognition system for Virtual Reality (VR) devices to take text input from users. An air-writing recognition system allows human users to write characters/symbols in the air as text input to VR devices. Inputing text has been a key challenge for VR systems because traditional text input mechanisms, such as keyboards, touch-screens, mouses, are particularly inconvenient for VR users. A system is device-free if it does not require users to wear any devices. With such a device-free air-writing recognition system, a user can easily input text for VR devices. The device-free air-write recognition pattern ensures the privacy information preserved [1] [2] because it has no access to collect individual sensitive information such as fingerprint, face. The key limitation of such schemes is that they are not device-free and thus inconvenient to use. WiFi signal based schemes use WiFi signals to recognize user handwritings. Sun et al. use the Arrived of Angle (AoA) information derived from WiFi signals to track user's hand movement [7]. The key limitation of this scheme is that the air-writing recognition is realized by a ready-made handwrite recognition application called MyScript so it lacks of the research on the features of letters and classification.

II LITERATURE SURVEY

In this paper, In recent years, researchers have proposed to use Wi-Fi signals for sensing purposes. Prior work has used Wi-Fi signals to detect the presence and location of an indoor human [10] – [12], to recognize gestures [13], [14], human activities and speech [15] – [17]; to count the number of people [18], [19]; and to identify human users [20] [21]. In 2013, Zhou et al. utilized the RSSI values to detect the presence of indoor humans [10]. In 2015, Abdelnasser et al. presented a system called WiGest, which uses RSSI fluctuations to recognize seven gesture families to control a media player application [14]. Due to the advent of CSI Tool in [22], we have access to the measurement of fine-grained CSI values, which are distinguished from the coarse valued RSSI. In 2017, Wang et al. proposed a fall detection system called WiFall, which utilizes finer-grained CSI to assist in elderly health supervision [23]. After that, Wang et al. presented a system called WiHear based on the claim that Wi-Fi signals can be used to determine what a person is saying by building mouth models for each syllable [17]. In 2016, Wang et al. proposed a novel authentication method by analyzing the CSI caused by people's unique walking gait [21]. Zeng analyzed the people's unique walking gaits to achieve identity authentication and proposed a system named WiWho [20] .the dynamics of overt visual attention shifts evoke certain patterns of responses in eye and head movements, in particular the interaction of eye gaze and head pose dynamics under various attention-switching conditions.

Sudden, bottom-up visual cues in the periphery evoke a different pattern of eye–head yaw dynamics as opposed to those during top-down, taskoriented attention shifts. In other interactive environments such as intelligent command-and-control centers or intelligent meeting rooms, systems monitoring the participants or operators could provide assistance based on the subjects' body language. This may help reduce distractions and help improve performance of whatever task is being performed. Landry, Sheridan, and Yufik (2001) discovered that certain patterns, or "gestalts," of aircraft on a radar screen drew the attention of the air traffic controllers due to their location, though they were not relevant to the task. An air traffic control training manual from the FAA (Cardosi, 1999) states that "even in low-workload conditions, distractions can clobber short-term or working memory." An assistance system could mitigate such dangerous situations by detecting the context of the attention shift and providing warnings when the attention shift is not task related [1].

In this work proposed the use of eye movement analysis as a novel modality for the recognition of physical activity. We devised 90 features specifically geared towards capturing a wide variety of eye movement characteristics. Using wearable EOG recordings from an eight participant study, we showed that we can recognize five different physical office activities from a continuous sequence. The importance of these findings lies in their fundamental significance for eye movement analysis to become a general tool for the recognition of human activity. The developed feature set and recognition methodology are not limited to the chosen setting, activities or eye tracking equipment. Instead, the current work shows that eye movement analysis has the potential to be successfully applied to many other activity recognition problems in a variety of different settings and for a broad range of visual and physical activities [2].

In this system, Recent studies have suggested the importance of semantic information in predicting human fixations. To reduce the semantic gap between model prediction and human behavior, we re-architect DNNs for object recognition to the task of saliency prediction. The fine-tune network with saliency metric as an objective function, and use information at multiple scales. This leads to a saliency prediction accuracy that significantly outperforms the state-of-the-art [3].

This paper addresses a novel virtual reality (VR) system that is based on the real world in which we live. The ultimate goal is to implement it as though a VR user freely exists in a place. To this end, it is most important to reconstruct a VR space that provides six degree-of-freedom (DOF), namely, yaw, pitch, roll, surge, sway, and heave. However, most currently released VR services that are based on the real world limit users' movements to three DOF. Even if the services support six DOF, most are highly complex and based on computer graphics. To overcome this problem, we first assume that there is a full Internet of things (IoT) infrastructure for collecting important data for VR space reconstruction. This assumption is realistic because many researchers expect that in the near future, IoT technology will lead to a world that connects not only people to people but also things to things. In this paper, we propose an end-to-end system architecture of the VR space that is based on the real world along with the elemental technologies that constitute the proposed system. This paper also includes a detailed survey of both conventional and emerging studies by other researchers [9].

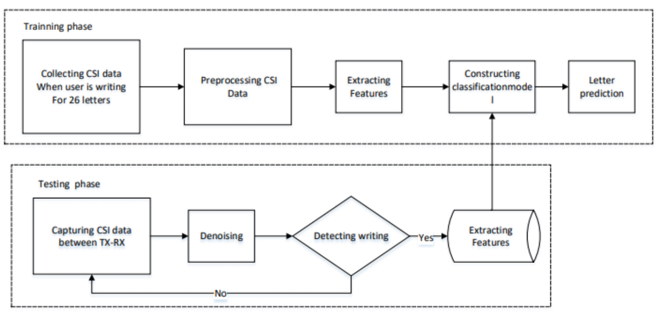
It is estimated that the number, position, size, and length of obsessions are elements of the metric utilized for scattering in a scattering based obsession recognition calculation, and additionally of the limit esteem. The affect ability of the I-DT calculation of the different free factors was resolved through the investigation of look information from chess players amid a memory review test. A methodology was followed in which check ways were created at unmistakable interims in a scope of edge esteems for every one of five unique measurements of scattering. The rate of purposes of respect (PORs) utilized, the quantity of obsessions restored, the spatial scattering of PORs inside obsessions, and the distinction between the sweep ways were utilized as pointers to decide an ideal edge esteem. It was discovered that an obsession span of 1º gives an edge that will guarantee applicable outcomes as far as the number and position of obsessions while using around 90% of the look information caught [4].

This paper displayed a novel profound learning engineering for saliency forecast. Our model takes a non-direct blend of medium and abnormal state highlights removed from a CNN, and a preceding applies to anticipated saliency maps, while as yet being trainable end-to-end. Subjective and quantitative correlations with best in class approaches show the viability of the proposition on the greatest dataset and on the most prevalent open benchmark for saliency forecast [5].

The proposed an intermittent blend thickness organize for spatiotemporal visual consideration. We demonstrated that our model beats cutting edge strategies for saliency expectation in recordings. We have additionally demonstrated that the saliency maps created by our model can be utilized to enhance activity classification utilizing an extremely basic methodology. This recommends saliency can improve the unique video portrayal. The runtime overhead to gauge the saliency outline little: just 0.01s added to the component extraction time of 0.07s. As future work, we intend to close the hole among RMDN and activity acknowledgment with a joint system. The thought is to have as yield of the model both the saliency delineate each time and the class of the activity for the whole video. This can be joined with utilizing the saliency delineate at the past time to weight the contribution for the current time. Assembling these two thoughts in a solitary system would result in a joint model for saliency forecast and activity acknowledgment [6].

III PROPOSED SYSTEM

The WriFi system works. The Wri-Fi consists of a router as the sender to emit WiFi signals, and a laptop with dedicate network card as the receiver to receive WiFi signals, as shown in Figure 1 and a user writes beside the LoS (Line of Sight) path. When a user writes characters/symbols in the air, the Chanel State Information (CSI) values that the receiver receives are impacted due to the multi-path effect of wireless signals. Because different character/symbols written by the user hand impact the CSI values differently, based on how the CSI values change, we recognize the character that the user writes In the data acquisition step, users perform air-writing in a unistroke and overlapped style, and the system collects CSI measurement at the mean time. In the data preprocessing step, WriFi adopts four steps to de-noise the collected CSI singals: normalization, covariance matrix calculation, eigen decomposition, and principal component calculation. In the action detection stage, WriFi applies a sliding window to the CSI stream to calculate the FFT-based motion energy as metric to discriminate four common indoor behaviours. In the feature extraction step, WriFi extracts the four kinds of waveform characteristics of 26 letters and resolves a letter into strokelevel to analyze the speed variation when writing ligatures. In the training step, WriFi builds 26 Hidden Markov Model (HMM)s, one for each individual English letter using features extracted from the denosied CSI values. In the testing step, WriFi first uses an energy indicator to detect the presence of a writing action, and then recognize this letter by fitting the letter to an HMM model that has the maximum likelihood to generate it. Unistroke and Overlapped Writing Style: We make two important assumptions in this paper. The first assumption is that WriFi users adopt the same writing style called unistroke. Unistroke is a writing style that requires the user to complete a letter in one continuous stroke. CSI measurement: WriFi collects Channel state information (CSI) measurements from the targeted device. CSI is a physical-layer information that are available in many commodity network interface cards, such as Intel 5300 and Atheros 9390.



VI CONCLUSION

In this paper make the following contributions. First, a novel air handwriting recognition framework without any other specialized sensors which meet the devicefree, low-cost and pervasive concept. We demonstrate that WiFi signals can also be used in distinguishing 26 individual capitalized English letters. We denoise the collected CSI data using PCA based denoising algorithm. The system detects the writing action persistently by FFT based energy indicator. After obtain the motion character data, the unique writing patterns of 26 letters result in the unique CSI waveforms, we extract the waveform characteristics to depict the waveform shape and DWT coefficients to represent current writing speed. The features provide the observation for building HMMs. As a result, the average accuracy of detection method reaches to 94.0%. In the case of 100 training samples written in larger space, the cross validation result reaches the highest, 88.74%.

In the future, we will continue to add the 10 digits 0-9 into the air-write recognition research. We will train separate models for the same letter to accommodate the diversity of the writing habits. Furthermore, the word-based air-write recognition will be explored deeply as well. Due to the Wi-Fi connection is not stable sometimes, so we consider to use the directional antenna for more stable connection and higher signal intensity.

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