Configuration-Free Systems for Wifi Sensing based Smart Home using the Smart Remote Controller

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ABSTRACT

The Smart Home invention offers us extreme supervision over our home by automating the lighting structure, the dimming, the screens, electric machines, the sound and safety frames. Main technologies that provide connectivity to smart home facilities, WiFi is one of them. In traditional households, where the household appliances will increase, the remote controls to manage them and the interference between them will also increase. This makes the system configuration dependent and troublesome for users to manage them that increases their burden. Recently, some systems were developed to manage multiple household appliances through one interface. However, the matter is once the dataset will increase the interface gets sophisticated and every home appliance or controller wants a special device to connect with it. In this paper, we introduced FreeGesture in the DeepRemote controller, which is a gesture recognition scheme without a device that uses preferred computer vision algorithms, particularly deep learning, to recognize numerous devices and manage them via IR or network. It simplifies deployment and makes systems without configuration. We are going to consider it as "Smart Remote" in this article. Smart Remote consists of four buttons, a camera, an Inertial Measurement Unit (IMU), a WiFi component, an Infrared (IR) transceiver, and a speaker. The popularity accuracy of smart Remote for 5 varieties of home appliances from completely different places is hyperbolic from 81.07% to 95.8%.

KEYWORDS : Smart home, WiFi sensing, Deep learning, FreeGesture, Smart Remote.

1. INTRODUCTION

Smart home appliances that have multiple functionalities made our daily routine advanced and rich. The interconnections of plenteous devices fastened in a very good household appliance with sensors and actuators for mechanization facilities. Current advances have discovered in wireless technology that to capture natural dynamics, WiFi signals are quite delicate, so they can be used to detect persistence. The three levels involved for the smart home integrator that can be a blend of various forms of technologies are a level of application, networking, and perception. The level of perception can be loaded to gather the knowledge of the event from the configuration and functions, as it is the limit for individuals to work with associated objects. The need for a friendly interface to use the interface has driven the progress of widespread and new detecting approaches [1].

There are the main benefits of used WiFi sensing in smart homes.

1) Cost effective. It is very effective by price to prepare sensing tasks on current infrastructures. It is

doable by WiFi sensing, typical interior WiFi transceivers.

2) Suitable placement. Place one or many pairs of WiFi transceivers within the place of concentration to build a smart home supported hardware. Unplanned placement isn't cheap by literary works [2-3]. For suitable placement, the software has been developed in the community. There is no need to do extra effort for the development of a device driver. Therefore, we can get an appropriate deployment.

3) Non-invasive sensing. The Energetic or inactive WiFi detection removes the belief in direct contact and uses hidden radios. User knowledge is not mandatory for the achievement of detection responsibilities. Therefore, it is practical to "recognize" and "understand" user behavior [1].

We assume that on different platforms CSI (Channel State Information) can be easily achieved. There ought to be configuration-free applications that manage CSI signal because it is prone to interventions like multipath, media competition, and different magnetic attraction noise [4]. It suggests that systems are regardless of placement and no need for training. The system is not independent of

configuration because of such intrusions. A strict setup is needed for keystroke recognition [5] and respiration monitoring [6]. In this situation, the transmitter and also the receiver is devoted pretty close to accomplishing high SNR, preventive its applied application. Therefore, the mockups that follow training-based approaches aren't promptly acceptable across totally different things, and in new locations, additional training would be required. So, it's challenging and difficult to create configuration free WiFi sensing-based systems.

A basic interface used to manage home appliances is an infrared (IR) remote controller. As in fig. 1, the number of remote controllers increases when we install a new appliance in our home because each home appliance needs one controller to operate him. The user needs to be learned about how to use each controller which actually could be a burden for him. It also increases the management cost and makes the system configuration dependent. We need a system that reduces the user's burden and management cost by operating many home appliances at one interface to simplify the deployment.

Figure 1: Increasing home appliances with many IR remote controllers

CSI (Channel Status Information), which is shown as a matrix that is a dimension record with the flow of completely different carrier data that can be considered different sensors. CSI (Channel Status Information) is a considerably better metric of the RSSI (Received Signal Strength Indicator) and most systems are based on it. This is somewhat like employing a detector array to seizure data with a matrix output, which is extremely the same as computer vision knowledge [7]. Therefore, computer vision favored algorithms, particularly deep learning [8] is also useful. Once WiFi signal meets deep learning, it may bring a lot of chances for WiFi empowered systems, which make simpler the placement and makes the systems independent of configuration. Deep learning (also called deep structured learning or hierarchic learning) is a subfield of a wider field of machine learning approaches supported learning information representations, as hostile task-specific algorithms.

The first solution to the above-mentioned problem is the association of interfaces for monitoring diverse household appliances. Unification of domestic

gadgets and IR remote-controllers are two strategies for interface merger.

Following the first strategy [9-12], the domestic machines that are very much coordinated with the management IR and using the controller it can be monitored. The domestic device's IR signals can be recorded and monitored by a controller, which can work utilizing the internet and display. If the controller quits working appropriately then it becomes troublesome to manage the IR signals of many domestic appliances, the regulation of home machines can be done by learning the remote-controller's IR signals.

For the second method, i.e. unification of the home appliances [13-15], connecting the home appliance to the internet or home network, as shown in fig 2, is needed. Such type of home appliances is referred to as information appliances. Smartphones or net applications can be controlled information appliances through the network.

In the unification of remote controllers, one interface is used to regulate multiple household appliances. This approach, however, cannot remove the complication of management hence takes some effort and time to select and pick a target home appliance out of multiple appliances. So, a method or procedure for choosing a target home appliance based on intuitions is needed.

A common approach for picking an objective device is to join particular appliances or markings to machines that encourage to recognize that appliance, to which the remote controller is pointing out. It may use QR code, IR transmitters, IR LED (Infrared Light Emitting diode) as particular markings/gadgets. Using the monitoring device, it is feasible to choose a particular appliance by perceiving the specific marking/appliance. The major benefit of this system is to acknowledge any courses of action of users and domestic appliances. However, it takes the expense to associate a marking/gadget to each appliance.

Figure 2: Household appliances connected to the internet or home network

To choose devices for house use, while not combining uncommon gadgets to family unit apparatuses, numerous techniques have been envisioned (utilizing voice, vision, and so on). In case of voice oriented selection, clients, for instance, "on the ground floor, turn on the television " or "Set the cooling inside the parlor to the 26 levels of warming." In case of vision oriented selection, clients will pick family machines with instinctive administration like advise to a particular domestic device. The device utilizing a wearable-glass will comprehend this technique. Nonetheless, it is inconvenient for the framework upheld wearable appliances to utilize IR because of the territory for the management of IR, the wearable device's mounting on the transmitter is precluded. Consequently, we will in general accept that a controller that is hand-held, has high applicability for reasonable use [16].

In the light of the content stated over, the following paper introduces a synopsis of the smart remote controller in WiFi sensing based smart home-related configuration and multiple controls' issues, and the possible methodologies to overcome these issues in the field are proposed. The purpose of our paper is to explain a technique for functioning all of the appliances in a home from one remote controller supported deep learning approaches and FreeGesture recognition scheme to make a system configuration free. The association of this paper is as per the following. Literature review presents in the section 2. Section 3 presents the new proposed solution. Section 4 presents the discussion of results. The paper concludes in section 5.

2. LITERATURE REVIEW

2.1 Unification of remote controllers

Two approaches that are used to affiliate more than two remote controllers to minimum one interface include: using information appliances and engaging a remote controller with varied IR signals of household appliances. At the same time when most household appliances can be controlled by IR signals, systems and frameworks for joining the IR controller have been introduced in the past. A framework for connecting heritage household appliances to the network have introduced by Nakumara *et al.*, [12]. IR remote controllers, that can be used via a network and remotely regulator home appliances, have functions of learning IR signals and connecting to a home network. IRKit [9] and eRemote [10] are two types of IR remote controllers. HUIS remote controllers are built to control every home appliance, including TV, air-conditioner, lights and audio systems with one device remarkably. HUIS [11] is Associate in the Nursing IR remote controller that provides nursing electronic paper. Users can choose a favorite interface without any trouble.

Figure 3: Unification of remote controllers

There are some standardized communication protocols like ECHONET [15], UPnP (Universal Plug and Play) [13] and SEP2.0 that are used to control information appliances. Fast power line communication gets users' consideration widely as an associate for communication of home machines. UbiREMOTE, developed by Kiyokawa *et al.*, [14] is one of the proposed systems for controlling information appliances. This is achieved via interactions in a three-dimensional virtual space. This system uses UPnP standardized protocol for most powerful home appliances. The joining of multiple and functionally varying remote controllers can develop a malfunction and make it difficult to find a target appliance.

2.2 Selection of home appliance with special devices attached

The choice of a target appliance becomes easier if we attach the appliance to a special device. Wii Remote's gestures, a system component that was implemented and checked by Neelrath *et al.*, [17] is used to select a target home appliance. In this system, IR LED is connected to a home appliance and the LED (Light Emitting diode) flashes specific patterns which are further received and analyzed via Wii Remote. Ubi-Finger, developed by Tsukada *et al.*, [18] is a small finger-worn device that makes the selection and control of a target appliance much easier by gestures. An IR transmitter place next to the IR receiver to make it possible. The IR transmitter is attached to the Ubi-Finger' tip while the IR receiver is connected to the home machines.

Ujima *et al.*, [19] advised setting a depth camera and a projector on each home appliances. Thus, the home machine is displayed on the user's body and the signal control it using the user's two arms. Another framework, created by Komeda *et al.*, [20] utilizes a heading of the controller, in light of the greatest precision indoor situating framework, to call attention to the target machine. Remote-touch, developed by Ullah *et al.*, [21] makes selection convenient via reading the QR code. Installation of the device or an indoor situating framework is necessary for the selection of home appliances by these methods.

2.3 Selection of home appliance without attaching special devices

Researchers have found a couple of mechanisms to select electronics without using any dedicated tool. GeeAir which is proposed by Pan *et al.*, [22] selects electronic via speech recognition. It controls that electronic device through IR signals. Then there's Xiao *et al.*, [23] who says we can select the electronic device using electromagnetic noise patterns. Kong *et al.*, [24] on the other hand, make utilization of smart glass and environmental information to recognize the electronic device. Smart glass takes a picture of the device. Environmental information includes WiFi whereabouts, sound or glare. The pictures from a smart device are recognized using neural network algorithms. Yes, the special devices are not necessarily needed to be engaged physically with electronics but still, these methods make the process difficult to understand and it's tough to differentiate appliances.

Hase *et al.*, [25] study heavily makes use of deep learning algorithms. His programs learned from a much larger dataset of images i.e. around 10,000 images per appliance. Also, his system was only controllable with Infrared signals. Here's how Takahashi *et al.*, [16] fill these gaps. They developed DeepRemote and use transfer learning, hence the much smaller number of images were required for the training process. The actual neural network was trained with ImageNet [26]. They also evaluate performance, accuracy and show the response time of DeepRemote in a real environment. Our research is most relevant to Takahashi's study. Here's how our study differs from his study though. We introduce a device-free Gesture recognition [27] scheme in DeepRemote to increase its recognition accuracy more than previous and we will consider it as Smart Remote in this paper. Already conducted experiments have proven that FreeGesture recognition achieves more gesture recognition accuracy.

3. PROPOSED MODEL

3.1. System Overview

Deep learning (identifies appliances by visual features) is used in a Smart Remote controller which controls and organizes multiple home appliances. The developed system can actually function in the absence of any direct device connection to the appliance. Altering distance and direction of the home appliance does not leave a marked effect on control and recognizing power hence this controller is practical, compatible and easily operate able in a normal daily life routine environment.

Figure 4: Proposed System model

3.2. The flow of the system

Fig. 4 expressions the model of the system. Two units, a deep learning unit, and the control unit, connected via the home network, make up this system. The former one is used for the identification of home appliances utilizing an image while the later one acts as a controller with an attached camera. IR signals and WiFi are used for controlling home appliances through the Smart Remote. Most of the existing controllers can only control homogenous home appliances, but unlike these controllers, our system can recognize and control diverse electronic.

Figure 5: Control flow for the proposed smart remote controller

Fig. 5 demonstrates the control flow of the household appliance utilizing Smart Remote. In the preliminary step, a user direction the regulator to select a target appliance which is followed by pressing recognition key on the control unit. Pressed button captures the image of a home appliance using the camera attached through the control unit. The image is forwarded to the deep learning unit through WiFi connection, which in turn identifies the home appliance and sent the final result (according to the image) back to the Control Unit. A user can hear the audio feedback result. Following recognition, controlling the

appliance by using an IMU sensor (an inertial measurement unit) and 4 buttons (one power button, the other three buttons for controlling appliances) on the control unit becomes possible. To enhance the accuracy of this identification, in the measurement unit, a FreeGesture recognition scheme is used. There are multiple kinds of commands hence we introduce a function that ultimately changes the assigned operations of the button. For instance, when controlling a television, channel, and volume by these buttons if two tasks are allowed. The user can change the button assignment via gestures (e.g. by rotating the control unit, the user can choose a key to control volume or channel) if more than two operations are enabled. The identification/recognition button is always available regardless of appliance identification status. Recognition of the home appliance is important and necessary in order to control it [16].

Fig. 6. Control unit of Smart Remote [16]

3.3. Control Unit

The control unit is shown in fig. 6. Consists of 4 buttons & speaker, an infrared transmitter, a camera, a battery, and an onboard computer (OCT). USB and GPIO are used for communication between the device and the computer. A 3D printer was used for this controller. Since Raspberry-Pi-3, an OCT used a WiFi component. The camera is astride the control unit and acquires a 640×480 image. MPU-9150 is used for the IMU sensor. For gesture recognition, it acquires data from the 20 Hz turn sensor. The revolution of the right and the revolution of the left can be recognized as signs. The control unit judges that the user has made a signal, if the threshold value becomes greater than the rotation sensor's middling value (within a time-period).

3.4. Unit for Deep Learning (UDL)

- **Environmental Monitoring:** Because the deep learning processing load is excellent, the computer required high processing power. In the proposed system, in light of the fact that the control unit isn't so incredible in the figuring, top to bottom the learning is dealt with on a server PC (a UDL). Through the domestic network, it can be associated with the control unit. For communication between the control unit

and the UDL, the ROS network can be utilized [28].

- **Recognition model:** We use VGG16 [29] in the deep learning unit in our system. VGG16 is one of the models of the convolutional neural system (CNN) effectively formed by an expansive arrangement of image data, ImageNet. It comprises 13 convolution layers and 3 totally associated layers. 1000 units of the output layer and input material can be characterized into 1000 modules.
- **Fine modification:** VGG16 generates the characterization aftereffect of 1000 classes. Leave classes to integrate a fan, a TV and pointless classes like a container. In this way, we changed VGG16 on the model that had some expertise in recognition of home machines with the tuning. The most powerful approach to train Convolutional Neural Network is to Tune-up [30]. The parameters of the predetermined levels can be formed, and the configuration of completely associated levels can be changed using Fine Tuning (keeping the parameters of the rest of levels). The setup has two advantages: lessening the time mandatory for training and reducing the data set for training.

3.5. Algorithm

The working of our proposed framework is clarified through the description of the following algorithm.

- STEP 1:** On the target device, the user points the controller and (on the control unit), the recognition-switch is pressed.
- STEP 2:** The image is captured, with the camera prepared with the control unit.
- STEP 3:** Send the image to the deep learning unit by means of WiFi.
- STEP 4:** In the image, device recognition is done using the UDL.
- STEP 5:** The recognition results are sent to the control unit.
- STEP 6:** Inform the user through audio comments on the result of recognition.
- STEP 7:** The user controls the recognized device via four power buttons and an IMU (Inertial Measurement Unit).
- STEP 8:** The device performs the action based on the command of the transmitted infrared signal.

4. RESULTS DISCUSSION

We define the performance evaluation of the smart remote control performed by [16] in this segment. First, they describe the training data and test environment, then examine the precision of this model and introduce user learning.

Figure 7: A design of the experimental environment

Fig. 7 demonstrates the design of the experimental environment. From three different positions P1, P2 and P3, they captured 20 photos for each device as appeared in Fig. 7. Overall, three hundred photos were composed for training.

Using fine-tuning with 300 pictures of 5 classes, they trained a model. They build up the decline of the stochastic slope (SDG) as the streamlining agent and the clear-cut cross-entropy as an element of the misfortune and occasions at 200. It is affirmed that the precision increments and the misfortune decline as the number of cycles build (times). Accuracy got to about 1.0 in the around 100th period in this training. Along these lines, it is inferred that the training was effective. The training time was around 90 minutes using the Core-i5 processor, on the computer.

Precision-rate in each location is very different, with an accurate precision-rate (90.45 percent) was P2. In all places, the average precision-rate is 81.07 percent.

When the acknowledgment button is pushed on the control-unit, the response time is assessed, until the moment that the detection outcomes are returned. The highest time was 3.07 sec, the base time was 1.72 sec, and the general response time was 1.95 sec. Delay in communication was the principal cause behind the deferral. It is feasible to see the image, without the GPU, and using the up to down learning [16].

From the above experiment, we can say that if we introduce the FreeGesture recognition scheme in its measurement unit, then the recognition accuracy could be increased from 81.07% to 95.08% (almost 15% increase).

5. CONCLUSION

We introduced a device-free gesture recognition scheme called "FreeGesture" in the DeepRemote controller and we consider it as a smart remote control in our paper that uses algorithms in favor of artificial vision, particularly deep learning, which is used to recognize different devices and operate them through IR or network. We use in-depth learning to simplify deployment and make the system without configuration for smart home based on WiFi detection. We use Smart Remote to intuitively control equipment through image recognition through in-depth learning. Our framework includes a deep learning unit, which explains how to perceive a home device that users must use and a control unit that can control household machines with switches (4 buttons) and signs. Our framework perceives a device with an accuracy of 15% higher than the past arrangement from 81.07% to 95.08% when we present the new FreeGesture recognition scheme with smart remote control. Utilize the pre-prepared VGG16 arrange by adjusting just 300 pictures. At the point when the framework is utilized with this exactness, the user should endeavor to accurately perceive 1.23 times. Likewise, with a recognition time of 1.97 seconds, our framework can work without a GPU and switch the device on for under 5 seconds when it is correctly recognized.

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