# Real Time Hand Gesture Recognition With A Novel Distance Measure GPD For IoT Based Controlled Assistance System

**Ch.NagaDeepa, Dr. N. Balaji, Dr. V. Padmaja**

**Abstract:** This paper focuses on developing a real-time hand gesture controlled assistive system (RTHGCAS) using Internet of Things (IoT) with a novel distance measure GPD (Gaussian Product based Distance). It is useful to the elderly people to communicate remotely for assistance and it provides continuous monitoring of the activities done by the user. To avail these advantages, person has to wear an embedded wrist wearable Assistive Gesture Recognition Device (AGRD). This AGRD performs an accelerometer sensor based hand gesture acquisition, recognition and communication. Initially AGRD need to be trained with different hand gesture patterns in the form of Random gestures, Telugu character vowels and English alphabets. We collected fifteen gesture patterns with five instances for training the device. By varying the sampling rate of the gesture signal, analyzed the RTHGCAS performance by considering recognition accuracy and application response time. The proposed algorithm with 50 Hz sampling rate is better for accelerometer based gesture recognition and real time action controlled with application response time of approximately 8.3 seconds, AGRD response time is of 9.54 milli seconds, and with a good accuracy of 97.38% which gives the better result when compared with Dynamic Time Warping distance measure.

**Keywords:** Accelerometer, Assistive living, Distance measure- GPD, Embedded AGRD, IoT, Real time hand gesture recognition.

## 1. INTRODUCTION

An elderly population in the world is increasing as a result of advances in technology, public health, nutrition and medicine. By 2050, percentage of people aged 60 or above will be doubled from now. With increase in population of aged people around the world, everyday support for the elderly people using Ambient Assisted Living (AAL) solutions has attracted the attention of scientists and health care providers. Aiding them to have an enhanced existence is significant and ensures abundant communal profits. Several researchers are functioning on different expertise such as helping robots for supporting aged people. The growing demand of maintainable healthcare methods has enlarged the significance for AAL progresses, produces and amenities. Latest developments in the Internet of Things (IoT) of the gadgets, gives an effective “Continuum of Care” along with assistance in all places. The primary target of ambient-assisted-living (AAL) focuses to give sufficient technological answers that would expand the feelings of personal satisfaction [2]. AAL uses mutually helping various stakeholders for avoiding mishaps along with checking old individuals in the household [8]. The customers will be observed continually, without the need for an individual to live with them [6]. In effect, an ongoing report [10] emphasizes on enhancement of the administration of health conditions, obtaining the response from remote places via medical attendants.


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The knowledge of human actions, conduct, and non-verbal communication is of clear significance in AAL applications. It can help in utilizing innovative answers for avoidance of medical hazards or observation and can likewise benefit the communication among the clients and the technological devices. IoT based medicinal service applications lay emphasis on the connection of all accessible resources in the society to perform healthcare events, for example, diagnosing, observing, remote help or medical procedures over the Internet. Numerous current IoT based healthcare approaches are using the four-layers which are Sensing, Network, Data and Application Layer.When managing old aged customers, it is essential to think about three vital attributes, i.e. usability, scope along with security in terms of privacy. As indicated from previous works evidence, three primary methodologies have been utilized as a part of activity recognition based on various sensing technologies environmental, vision along with wearable sensors. Technologies based on vision sensing bring up concerns related to security, illumination changes, occlusion and change in the background. The next method depends on the communication between user with objects, presuming that the utilization of specific object is entirely related to a precise activity, yet needs a lot of sensors which should be set up at the user’s place [1]. Smart bands offer open doors for pervasive computing uses which are reactive to the user’s observed condition and the neighboring atmosphere. The utilization of accelerometer information gathered by a smart band is especially helpful for recognizing activities whenever performed by the operator. Action acknowledgment is a critical exploration issue in pervasive computing, which is broadly studied in the mentioned papers [17], [13], [14], [7]. The utilization of wearable sensors provides the potential to gather information about user movements neither making them to remain in front of vision related gesture capturing device nor make them interact with depth camera [4]. Many studies concentrated on wearable human activity recognition [18]. Most of them are used unsupervised learning that use unlabeled dataset which is difficult to generate and requires updating and addition to the database whenever a new motion is performed [16]. In [3] two dimensional gestures based Telugu character recognition was done with accelerometer data using machine learning algorithm in simulation environment. In data mining concepts [19] of IoT technology they proposed Gaussian based similarity measurement. We adopted that technique and proposed a novel distance measure for real time hand gesture recognition. The proposed system works in real time environment and is helpful to elderly people for assistance using simple hand gestures.

The major contributions of the research work are as follows.

1. An Assistive Gesture Recognition Device (AGRD) is developed for capturing and recognizes the hand gesture performed by the elderly people.
2. A resource-aware continuous hand gesture recognition and activity recognition algorithm was developed.
3. To establish a communication link from elder person to the caretaker Smart phone, an IOT framework was developed.
4. A novel distance measure GPD was proposed for classifying the test gesture pattern.
5. With three categorical gestural pattern datasets RTHGCAS was tested.
6. The performance of RTHGCAS was analyzed by considering the metrics of recognition accuracy and AGRD response time and application response time.

## 2. REAL TIME HAND GESTURE CONTROLLED ASSISTIVE SYSTEM

Assistive living system increases the quality of life by monitoring elderly people at home and preventing accidents. Often, elderly people who can't speak or bedridden, they have to rely on others for assistance. For them an application was developed as real time hand gesture controlled assistive system using IoT (RTHGCAS) and is shown in Fig.1. AGRD device can be placed on user's wrist for recognizing hand movement signals and these gesture signals are used for assistance.

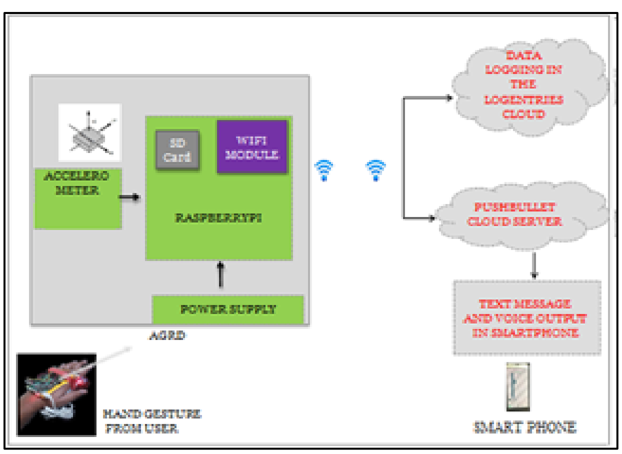



***Fig.1*** *Architecture of RTHGCAS*

## 3. METHODOLOGY FOR RTHGCAS

RTHGCAS is mainly executing three tasks named as hand gesture acquisition, gesture recognition and sending gesture mapped meaning to the caretaker's smart phone. These three tasks can be scheduled by AGRD which is an embedded wrist wearable device. AGRD contains an ARM processor which captures the measured digital vectored accelerometer signals produced by the inertial sensor module over an I2C interface. Accelerometer mainly provides the advantages of low power consumption and meets high performance necessities of wearable sensors. Dimensionality of AGRD is about the size of 10 cm × 7 cm × 5 cm. Device is placed on the wrist of the elderly person. 3-axis accelerometer values are used for gesture recognition. Accelerometer measures the motion accelerations of hand movements and holds the user selectable full-scale value of ±2g, ±4g, ±8g or ±16g. Further, the device initializes +/- 2g which is the most sensitive setting for an accelerometer. Sampling rate of 50 Hz is used for high accuracy gesture recognition. When hand gesture is performed by the user with wrist wearable AGRD device, ARM processor with an accelerometer sensor acquires hand gesture data which deals with the necessary signal preprocessing and recognition steps further.

### 3.1 Gesture Acquisition

There is no publicly available gesture dataset for the evaluation of 3-Dimenional gestures using accelerometer sensor. Hence our own gesture data set was created which contains Random gestures, Gesture in the form of Telugu characters and Gesture in the form of English alphabets. For this paper we consider all the gestures are of single trace. The constraint for hand gesture creation by the user as: Gesture starts with a dot and ends with an arrow mark which is shown in the Table 1, 2 and 3.

***Table. 1.*** *Random Gesture pattern*

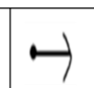
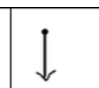
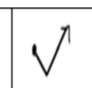
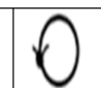
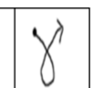
| Gesture pattern |  |  |  |  |  |
|---|---|---|---|---|---|
| Gesture Label | Right | Down | Tick | Circle | r |

***Table. 2.*** *ENGLISH alphabet Gesture pattern*

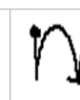
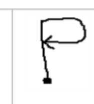
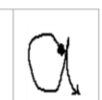
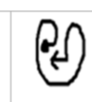
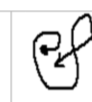
| Gesture pattern |  |  |  |  |  |
|---|---|---|---|---|---|
| Gesture Label | n | d | e | p | a |

***Table. 3.*** *TELUGU vowel Gesture pattern*

| Gesture pattern |  |  |  |  |  |
|---|---|---|---|---|---|
| Gesture Label | aa | aaa | ee | eee | ka |

If the user want to give notification to the care taker, in native language like Telugu or English, then user can use gestures which are shown in Table 2 and 3. In that gestures are labeled with a name. All gesture patterns are simple and single stroked for ease of performance by older people in real time. For training AGRD, fifteen gestures have performed and each gesture repeated for five times by the user. The total training set contains seventy five gesture instances, which are stored in memory SD card for recognition process. These gesture movements that were used in this application are for assisted living. These gestures were also chosen because they are similar to each other and involve the convenient use of hand motion. AGRD is designed to facilitate personalized gesture recognition based on user's choice. Data were acquired using single sensor unit placed on the wrist. Each gesture has n*3 matrix values where each column represents the acceleration in the x, y and z-direction. Here 'n' represents the length of the gesture sequence. The Fig 2 shows graphical variation in all three axes for "down" gesture. Accelerometer sensor senses the rate of change of acceleration which is measured in meter per second square ($m/s^2$) units. Since the motion inputs are sampled at 50Hz frequency and each gesture is captured using only one second window. Hence, per gesture fifty samples in each x-axis, y-axis and z-axis. The graph represents the sample number on x-axis and acceleration values on y-axis. In graph from ten to twenty five samples on x-axis, there is a

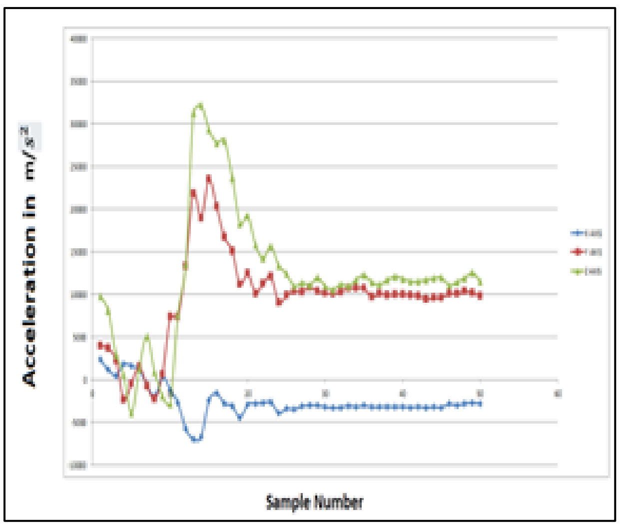



***Fig. 2*** *Gesture Acquisition signal for "Down" pattern*

considerable variation, shows the characteristics of the gesture.

### 3.2 Real Time Hand Gesture Recognition based on GPD classifier

Basic modules of a recognition algorithm are preprocessing, dynamic time warping algorithm, and template adaptation. Algorithms principle categorizes the human motion using series of time based on forces applied to the AGRD having a single three-axis accelerometer and identification of gesture was done by similarity matching between two time series templates at a time. A database was created by storing time series templates for each gesture separately which is given as input from the user. Database acts as a template scaled for recognition. The input for algorithm is a time series of acceleration delivered using one accelerometer having three axes. Every gesture trace will be in the form of an array consisting of three columns each representing the acceleration along the three axes. Stored templates in the database were also scaled in parallel. This algorithm includes filtering the vectored acceleration information and scaling the data within 0 to 100. Further, Gaussian product distance measure (GPD) compares and matches the time series values of current test gesture against the gesture vocabulary templates in the database. Gesture is recognized as a template which has the best similarity matching and least distance after applying GPD. This recognition algorithm contains two sub sections, training stage and testing stage. In both the stages the sensor data has to be preprocessed. When a new test input is given, it is preprocessed and measures the distance with trained database with GPD distance measure. If the test gesture is matched with trained database then it gives the output as predicted gesture.

#### 3.2.1. Pre-Processing

Hand gestures are acquired from the accelerometer sensor analog to digital conversion which produces high frequency quantization noise. Internally low pass filtering is done to remove this noise with a bandwidth of 21Hz. To satisfy nyquist criteria, a sampling frequency of 50Hz has been selected. In general, the signal returned by the accelerometer is quite noisy. In order to reduce the effects of noise that may adversely affect the recognition results, the gesture data were further smoothed by using a five-point moving average filter with window length as five. Since the range of values of raw data varies widely over a range, hence scaling is used.

#### 3.2.2. Proposed Gaussian Product Distance based classifier

In the proposed 3-axis accelerometer gesture recognition system, since each gesture trace is defined by three acceleration waveforms that is x-axis, y-axis and z-axis. The similarity cost between test gesture trace $G_i$ of size n×3 and trained gesture trace $G_j$ of size m×3 is computed. In this paper, sampling has been done at 50Hz frequency so each gesture has 50 samples, with 3 columns therefore n = m = 50. For each column we compute the distance. For example a gesture test sequence for x-axis is given as $G_{\text{test(x-axis)}}$ in equation 1. Stored gesture template sequence in database for x axis is given as $G_{\text{train (x-axis)}}$ as described in equation 2.

$$G_{test(x-axis)} = [G_{t1,}G_{t2}, G_{t3} \cdots \ G_{tn} \ ] \qquad \text{--(1)}$$

$$G_{train(x-axis)} = [G_{tr1,}G_{tr2}, G_{tr3} \cdots \ G_{trm} \ ] \qquad \text{--(2)}$$

$$standard\ deviation\ \sigma_{ftrain(x-axis)} = [\sigma_{f1,}\sigma_{f2}, \cdots \ \sigma_{fn} \ ] \qquad \text{--(3)}$$

To compute the similarity between tests gesture with trained gestures the following steps need to follow.

**Step1:** For all the trained gesture template, x-axis values obtain the standard deviation as $\sigma_{f1,}\ \sigma_{f2..,}$ . Generate the standard deviation trained vector as in equation 3.

**Step2:** Compute the average similarity of test x-vector and trained x-vector by using the equation 4 to get the average similarity.

$$\text{Gaussian product average similarity} = \prod_{i=1}^{n} e^{-\frac{1}{n}\left(\frac{G_t(i)-G_{tr}(i)}{\sigma_f(i)}\right)^2} \qquad -(4)$$

**Step 3:** Calculate the similarity value by using equation 5.

$$\text{Simi} = \frac{GPAS+0.367879}{1+0.367879} \qquad \text{--}(5)$$

**Step 4:** Compute the Gaussian Product based distance by using equation 6.

$$GPD = 1 - Simi \qquad \text{--}(6)$$

**Step 5:** Repeat the steps 1 to 4 for the y-axis vector and z-axis vector. When GPD computed cost between two Gesture traces in x, y, and z axes is equal to zero means those gestures are similar otherwise those gestures are not similar.

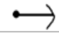
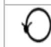
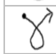
### 3.2.3 Testing

The test gesture undergoes all the pre-processing steps before the distance measure is calculated using GPD measure. In order to recognize an unknown gesture trace Y, it is intuitive to compare it to the set of exemplars in E (trained gestures) and classify Y to the gesture whose exemplar gives the lowest cost. The proposed recognizer comprises mainly of two steps. In the first step, the unknown gesture trace Y is compared to the set of exemplars obtained in the training stage to find those that are closest to Y. Then, the functioning is created in such a way that the each gesture in the database falls under a group, if the test gesture obtains least distance measure with a gesture in the database then the class related to that database gesture is considered as test gesture class. If test gesture is matched with any trained gestures then call the function related to sending text and voice message related to the corresponding gesture.

### 3.3 GESTURE CONTROLLED ASSISTANCE SYSTEM

If any gesture is created by elder user, the system provides two cloud based services. One it provides continuous logged information about elder person status. Second system provides user intension is send to the caretaker Smartphone as a text message and voice message. An application runs on the android device which is the smart phone on caretaker's side. Android application provides the interface to the caretaker, receives the equivalent meaning from the wearable device in the form of text message and voice generation which was described in Table 4. The cloud logging of the equivalent meaning with date and time stamps is done to know the status of the elder person. AGRD and registered Smartphone communicate using Wi-Fi. This application is developed using Python, cpp and cloud based services. In this system we used two clouds. One for notification to smart phone about the AGRD user's intension and second cloud is for continuous monitoring the user activity in server.

***Table. 4**. Random gesture mapping with Text message*

| Random Gesture | Gesture Label | Message Send To Smart Phone |
|---|---|---|
|  | Right | I am Thirsty |
|  | Down | Make me to Sit |
|  | Tick | Take me to washroom |
|  | Circle | I am Hungry |
|  | Wrong | I am Feeling Sick |

For example an elder people use random hand gesture pattern which was described in table 4, he conveys a message to the care taker's smart phone using IoT based cloud services.

## 4. RESULTS AND ANAYSIS of RTHGCAS

A real-time hand gesture controlled assistive system (RTHGCAS) using Internet of Things (IoT) is developed using an embedded wrist wearable device.

### 4.1 Recognition with Gaussian Product distance measure (GPD)

GPD can measure the distance between test gesture with trained gestures. The measurement of Gaussian Product Distance between the five gesture classes which are in the form of Telugu vowel gesture patterns by using distance measure GPD described in Table 5. By using this measure, test gesture is going to predict the class label and with this user convey their intensions in their native language.

***Table. 5:** GPD distance values TELUGU vowels Gesture patterns*

| GPD distance matrix | | | | | |
|---|---|---|---|---|---|
| | aa | aaa | ee | eee | ka |
| aa | 0 | 0.64177 | 0.41812 | 0.71111 | 0.59319 |
| aaa | 0.64177 | 0 | 0.43368 | 0.67455 | 0.64459 |
| ee | 0.41812 | 0.43368 | 0 | 0.66152 | 0.50574 |
| eee | 0.71111 | 0.67455 | 0.66152 | 0 | 0.67961 |
| ka | 0.59319 | 0.64459 | 0.50574 | 0.67961 | 0 |

### 4.2 Real Time Alerts on Smart phone

AGRD will send a voice and text message to Smartphone using push bullet app, by using cloud services and acts as a message broker to direct the message in the form of text which is a notification to the caretaker from the AGRD. When gesture is performed by the user, AGRD will recognize the gesture and corresponding meaning is send to the caretaker's Smartphone immediately within few seconds which is shown in the figure 3. When AGRD's power supply is ON, device continuously scans the user to check whether any gesture is performed or not. Whenever any gesture is performed by user who wears the device, AGRD logs the status or activity done by the user and is stored in the cloud server. Until the device is OFF, the setup will be in the state of continuously monitoring the person activities. Hence RTHGCAS is also used for activity recognition.

### 4.3 Text to Speech Output on Smart phone

Speaki app reads out loud the received notifications on the mobile. The intention of the gesture performed by the dumb person can be easily understood with voice output which reduces the communication gap between the mute community and standard world. Default Text-To-Speech engine must be the smart phone. Speaki app provides privacy and control about when the notification is to be read.

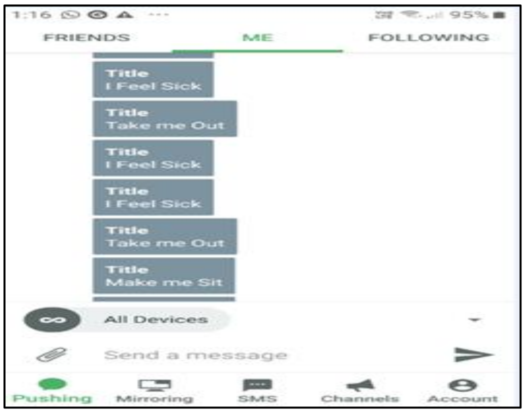



***Fig.3**. User Intension alert message to caretaker*

### 4.4 Performance Analysis

The Real Time Hand Gesture Controlled Assistive System (RTHGCAS) performance is measured in terms of recognition accuracy, application response time (ART) and AGRD response time (GRT) by using equations 7, 8 and 9. Where time taken for gesture recognition in AGRD is called as GRT and the time taken for receiving the notification in care taker's smart phone is called as ART. After training AGRD, check the RTHGCAS performance with a new test input.

$$\text{ART} = \text{GRT} + \text{message Transmission to Smartphone} \quad \text{-- (7)}$$

$$\text{GRT} = \sum (\text{Acquisition time, recognition time}) \quad \text{-- (8)}$$

$$\text{Recognition Accuracy} = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad \text{-- (9)}$$

Recognition accuracy was calculated using equation 9 which states that the proportion of the total number of predictions that were correct. The notations TP, FP, FN, TN represent "true positive", "false positive", "false negative", and "true negative" respectively.

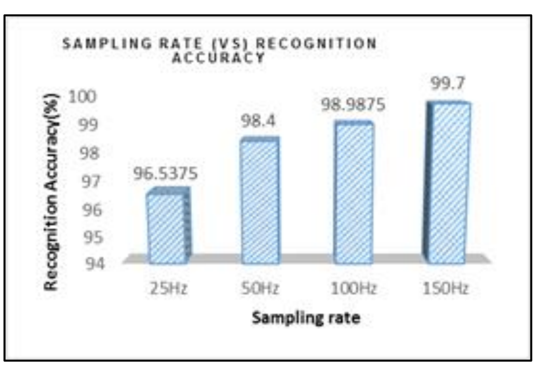



***Fig. 4**. Sampling rate Versus Recognition accuracy for random gestures*

In real time applications, it is necessary that the hand gesture controlled assistive system responds in time with good accuracy. The application response time is the time taken for the system to send the user intension in the form of text and voice message to the caretaker's smart phone using the cloud services within a particular period of time. It also depends on factors like signal strength, network delay, connectivity issues.

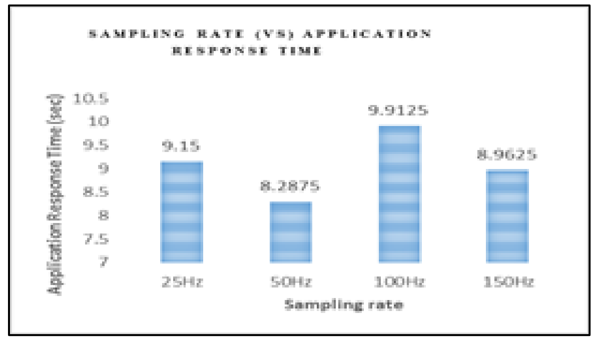



***Fig. 5**. Sampling rate Versus ART for Random gesture patterns*

Experiments were conducted on random gestures which are shown in Table 1 with various sampling rates 20 Hz, 50 Hz, 100 Hz and 150 Hz. Average recognition accuracy and average Application response times are calculated for each Random gesture pattern with different sampling rate which are shown in figures 4 and 5. Application response time of RTHGCAS is calculated with different sampling rates. Lesser the application response time, faster the application works and vice versa. Finally 50Hz is selected as device's frequency to get faster real time event based alerts. RTHGCAS works well with proposed recognition algorithm for the user defined patterns in the form of Random gestures, Gesture based Telugu vowels, Gesture based English alphabets with a recognition accuracy of 97.38% and application response time is of 8.25 seconds which is shown in Table 6.

***Table 6:** Performance analysis of RTHGCAS*

| Gesture Pattern | Number of Gestures | Gesture Recognition accuracy (%) | Application Response Time(ART) (sec) |
|---|---|---|---|
| Random gesture | 5 | 98.40 | 8.28 |
| Telugu Vowel Gesture | 5 | 95.15 | 8.02 |
| English alphabet Gesture | 5 | 98.66 | 8.46 |
| Overall performance of RTHGCAS | | 97.38 % | 8.25 sec |

## 5. CONCLUSION

In this research, we proposed a distance based classifier for real time hand gesture recognition. For this real time wrist wearable accelerometer sensor based Assistive Gesture Recognition Device (AGRD) is developed for gesture acquisition, recognition of hand gestures performed by elderly people. It provides natural, efficient and flexible communication link from the user to the caretaker wirelessly using IoT. A software workflow was proposed for real time gesture recognition, real time notification and logging in the web. One of the major developments is Real time notifications with voice output obtained on smart phone as soon as the gesture is performed. We conclude that sampling rate affects the recognition accuracy and also it effects the application response time. At 50Hz, sampling rate system shows faster response to gestures performed by the elder person when compared to other sampling rate response times. Experimental outcomes are achieved an overall performance measure of about 97.38% recognition accuracy and overall application response time is about 8.25 seconds for fifteen gestures with less training data and with sampling rate of 50 Hz. At user side AGRD device response time is very less, which is 9.54 msec. This research overcomes the switch limitation without the need of start and stop sign for gesture acquisition. Hence RTHGCAS with novel distance measure GPD algorithm works better for fast and continuous gesture recognition and for controlling the assistive system with real time alerts using IoT.

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