Development of Available IoT Data Collection Devices to Evaluate Basic Emotions

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Abstract: For most users, everyday objects are connected to the Internet, using their computational capabilities to form a whole entity, called the ***IoT*** *(Internet of Things). This article deals with the creation of an available IoT device, with which we will be able to classify the emotional states of the user. Using existing technical solutions and methods that use approaches based on the application of sensors while maintaining their non-invasiveness, we have created such a device. In the analysis of the current state, we describe the possibilities of classifying human emotions, existing classification methods and how the measured data are related to human emotions. Next, we describe the methods used to analyze the collected human physiological signals. We propose a complex system for measuring physiological human signals and subsequent recognition of emotional states. We describe the composition of the proposed system, as well as the specific hardware and software used. At the end, we focus on the functionality and testing of the proposed system. Finally, we perform several measurements, where we evaluate their results and the reliability of the proposed system.*

Keywords: Internet of Things; emotions; data; sensors; heart rate; facial recognition

1 Introduction

Emotion recognition can serve as a scientific foundation for tracking emotional well-being and detecting the physiological and mental diseases linked to emotions. Emotions are conveyed in a variety of ways, including psychological behavior and physiological changes. Humans have no conscious control over these physiological changes. Thus, physiological signals can more objectively reflect participants' genuine feelings [1].

The Internet of Things (IoT) is a new Internet revolution and a developing research topic. The Internet of Things is always changing. A variety of methodologies and concepts from related technologies such as cloud computing, the internet of the future, big data [2], robotics, and semantic technologies [3] [4] are used to assess further possibilities. The Internet of Things (IoT) has a lot of potential in healthcare. Sensors that can measure and monitor a variety of medical characteristics in the human body can be used [5]. For example automatic recognition of emotions is usually performed by measuring various parameters of the human body or electrical impulses in the nervous system and analyzing their changes [6].

The Internet of Things is evolving at a rapid pace and remains the latest and most popular concept in the world of information technology. The Internet of Things can also be seen as a global network that enables communication between people, people and things all around the world, and gives each object a unique identity [7]. The concept of the Internet of Things, created by Ashton in 1999, has attracted and continues to attract a wealth of research and industrial interest [8]. The IoT ecosystem platform can in principle be divided into three layers, namely the sensor layer (for data generation), the communication layer (for connection and data transmission) and the layer of management (for data collection, storage, modification and management) [9]. Thanks to advances in the Internet of Things, it is possible to monitor the environment as well as users and their behavior at a very detailed level, reflecting their individual preferences [10]. Skin conductance (SC), heart rate variability (HRV), skin temperature (SKT), peripheral plethysmography (PPG), and other commercial monitoring equipment have been created to read human bio-signals [11]. One of the most crucial aspects of one's own personal health care is health monitoring. It is critical for gathering information about the user's circumstance. Fitness trackers, smart fitness bands, and portable ECG sensors are examples of health care monitoring devices. Companies can make better decisions when identifying a user's poor health because this data is constantly collected. Complex systems can now be implemented on small devices thanks to the Internet of Things [12]. We can only examine and calculate this data for our own needs with the help of a smartphone or a computer [13]. Sensors have shrunk in size, enabling for the creation of a wide range of wearable devices [14].

The article deals with the development of a compact device and the implementation of an effective health monitoring system based on IoT. The suggested system monitors critical human health metrics such as heart rate combined with face detection with the ability to wirelessly communicate the collected data to a database over Wi-Fi. A web application or a mobile application can be used to access the received data at any time.

2 Related Work

An integral part of these tasks are our smartbands and smartphones, which allow us to make life easier by controlling devices and storing important information, while displaying information about their status in real time on other devices [15]. Each device has its own UID with which it can recognize and transmit data over the network without requiring interaction between the user and the computer [16]. Smart devices based on wireless communication, through which information is sent from sensors, have been designed for ubiquitous monitoring of health and activity [17]. Smart devices can be used to monitor activities, health, sports and fitness [18]. Because there are many of these functions, it is impossible to capture a unique signal that can provide a good compressed system for variable analysis [19]. Cheng et al. designed smart clothing based on cloud and IoT technology for next generation healthcare systems [20]. This study presented a proposal for a practical mechanism based on computational technology for the analysis of emotions using predictive models in controllable interactions. The results showed that the use of components to collect physiological data and obtaining the results of analyzes of the patient's emotional state provided by cloud, machine intelligence and wearable devices can significantly improve the quality of experiences and services for users [21] [22]. A perfect emotion recognition system [23] would need a huge number of sensors and would still evaluate data inaccurately. It is due to the complexity of expressing these emotions, at the same time people themselves are unique in expression, gesticulation and facial expressions. The research used audio and video recordings as experimental materials to collect ECG electrocardiogram signals, pulse signals, skin temperature, and skin conductivity signals for emotion recognition research, and the results showed that the rate of emotion recognition decreased significantly with increasing emotion types [24]. GSR signals, heart rate and temperature were used to recognize emotional states [25].

2.1 Emotional States and Facial Recognition

The study of human emotions and their proper determination has been a research area in psychology since the time of Charles Darwin. However, from the perspective of computer science, it is a relatively new area of inquiry that has been jointly developed since about the 1960s. The merging of computer science and psychology in the context of determining emotional states is primarily related to the design of the first algorithm that provided face recognition [26]. However, the first functional fully automatic system is considered to be the one made by Kanade in 1973 [27].

In the context of linking the research fields of psychology and computer science, over the following decades, a number of different studies have confirmed the link between evoked emotional states and their characteristic expressions in the human face [28-33]. From the perspective of psychology, a number of different models have been defined that allow us to classify emotional states [34] [35], but two in particular have been most prominent and are currently the most dominant: Ekman’s classification [36] and the Russell Circumplex model [37].

Ekman’s classification is a model that is mainly applied in the context of direct observation of an individual's face (e.g., using a webcam). In the field of computer vision research, different methods are used in the context of Ekman classification for different phases of the recognition process. In particular, the most common method for the detection phase is the use of the Viola-Jones algorithm [38-41].

However, classifying the emotional state only from the face of the observed individual has several shortcomings. Ekman's model is very strict; it does not consider the so-called dynamic multimodal behavioral patterns in the individual under study. On the contrary, Russell's model assumes that, under certain conditions, there may be overlapping of some features that could clearly classify a given type of emotion (e.g., happiness and surprise, fear and sadness...). Therefore, several authors state that in order to be able to classify an emotional state unambiguously, it is necessary to consider other factors as well. Such factors are, for example, changes in physiological processes [42] [43].

2.2 Emotional States and Physiological Functions

Human emotions can be identified by facial expression, speech, behavior or physiological signals. However, the first three methods of recognizing emotions are subjective. For example, study subjects may intentionally conceal their true feelings, which may be inconsistent with their performance. In contrast, recognizing emotions using physiological functions is more reliable and objective.

Wearable sensors and various modules along with microcontrollers and microcomputers can be used to collect physiological features that we can use for the classification of emotional states. Collected signals can be:

- Galvanic skin resistance (Galvanic Skin Resistance - GSR)
- Electrocardiography (EKG)
- Heart rate (Heart Rate - HR)

- Electromyography (EMG)
- Body temperature

Galvanic Skin Resistance

There are specific sweat glands that cause a change in skin conductance and lead to GSR. These sweat glands, located in the palms and soles, respond to psychological stimulation rather than changes in body temperature [44] between GSR and arousal is a linear correlation [45] and reflects emotional reactions as well as cognitive activity [46].

Electrocardiograms (ECG)

They measure the electrical activity of the heart. Heart rate can be calculated from ECG [47] and it reflects emotional activity and is used to distinguish emotions (positive and negative).

Body Temperature

Normal body temperature (normothermia, euthermia) is a typical temperature range found in humans. The normal human body temperature range is usually listed between 36.5 and 37°C (97.7 – 98.6°F). Human body temperature varies. It depends on gender, age, level of physical activity, state of health, in which part of the body the measurement is performed, state of consciousness and emotions. Body temperature is maintained within a normal range by thermoregulation, in which temperature regulation is initiated by the central nervous system [48].

3 Materials and Methods

The aim of the article is to design and create a system for identifying and classifying the emotional state of the user using available IoT devices and to create a system for monitoring basic vital functions while maintaining non-invasiveness. Our goal is to create a system that can measure and process human physiological signals and use them to display results in the user interface. The system will also be able to determine from the acquired image from the connected camera focused on the user's face, what emotion is the user feeling based on an API cloud solution, in which it is not necessary for the microcomputer to perform complex calculations in neural networks.

Recent studies have shown that physiological signals contribute to the recognition of emotions. In an article by Wiem and Lachari [49], the authors focus on the classification of affective states into two defined classes in the arousal / valence model using peripheral physiological signals. To this end, they examined the multimodal MAHNOB-HCI database, which contains the body reactions of 24 participants to 20 affective videos. After pre-processing the data and extracting the functions, the emotions were classified using the Support Vector Machine (SVM) technique. The classification level was implemented on Raspberry Pi III model B using Python.

In the proposed approach, Wiem and Lachiri [49] used the recent Raspberry Pi III model. In addition, it allows machines to identify and recognize emotional states of affective interaction with humans. In addition, various ports, Bluetooth and Wi-Fi modules make it easy to interact with vulnerable people and children with autism who have physiologically wearable sensors.

They used the latest multimodal MAHNOB-HCI database for evaluation, which is freely available to researchers. After a preprocess phase followed by element extraction, they implemented a classification step on a Raspberry Pi III model B (ARMv8-A, 1 GB SDRAM). They divided emotion into two defined classes in the arousal and valence dimension, which are most commonly used in related works. Two classes are considered, which are "high" and "low" in arousal, "negative" and "positive" in valence.

3.1 Recognition of Human Emotions Based on Facial Images

The importance of facial expressions in determining a person's emotions cannot be overstated. It was discovered that just a little amount of research has gone towards recognizing emotions in real time using photos. Suchitra, Suja, and Tripathi offer a method for identifying emotions in real time from a face in a paper. They employ three phases to detect a face in the suggested technique [50]:

- Haar cascade
- Extraction of elements using the active shape model (ASM)
- The Adaboost classifier, to classify five emotions (anger, disgust, happiness, neutrality and surprise).

In a social services context where emotion recognition is important, the Raspberry Pi II is mounted to a mobile robot that can dynamically recognize emotions in real time.

A camera captures the real-time input image, which is then supplied as input to the emotion recognition software. The Raspberry Pi II runs emotion recognition software, which generates a list of categorized emotions as an output. On the monitor, the detected emotion is presented (Figure 1). The proposed approach is very valuable for society in a variety of applications where emotion recognition is important.

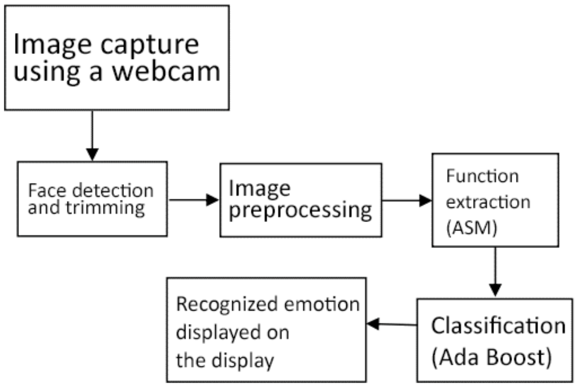

Figure 1
Illustrated wiring diagram (own figure)

3.2 Specification of the System

The measuring device consists of a Raspberry Pi microcomputer, an Arduino Uno microcontroller a MLX90640 thermal camera, a NoIR camera V2, a GSR sensor and Fitbit Sense fitness tracker. The thermal camera and the NoIR camera are connected to the Raspberry Pi, while the GSR sensor is connected to the Arduino Uno. The architecture of the proposed system can be seen in the figure (Figure 2).

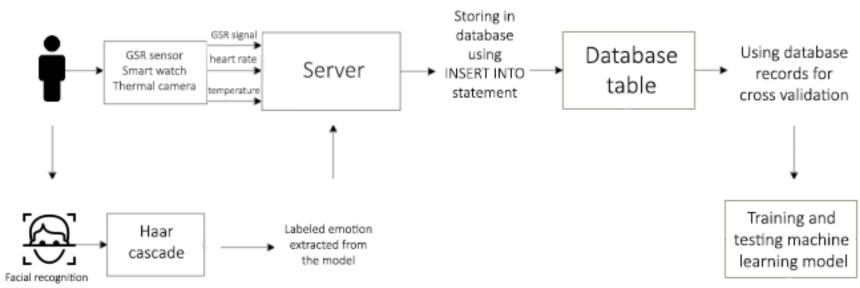

Figure 2
Proposed system architecture of the created system (own figure)

3.3 Classifying Human Emotions

Recognizing emotions by using facial recognition features can be done by using A. Balaji's [51] library. To recognize basic emotions, the program also adopts Ekman's [52] classification commonly known as "The Big Six." Happiness, sadness, fear, surprise, anger, and disgust were among the emotions, and they are still the most widely acknowledged contenders for basic emotions among emotion theorists [53]. In the event that the model is unable to detect any of the six basic emotional states, a seventh emotional state – a neutral state – is added to the classification. In order to use the model, it requires the following dependencies to be installed on the Raspberry Pi:

- Python version 3 (we used Python 3.6)
- OpenCV (Computer Vision)
- Tensorflow

35887 images of faces from the Facial Expression Recognition 2013 (FER-2013) dataset were used to train the machine learning model [54]. This dataset contains 48x48 grayscale photos that have been labeled with the emotion expressed. The figure depicts a random sample (Figure 3).

Figure 3
FER-2013 dataset image samples [55]

The model detects faces in each frame of the camera stream using the haar cascade method. Paul Viola and Michael Jones suggested an effective object recognition approach employing a cascade classifier based on Haar features in their 2001 paper "Rapid Object Detection with a Boosted Cascade of Simple Features" [56]. A cascade function is trained from several photos in this method, which is based on machine learning (positive and negative). As seen in the Figure 4, the classified emotion is overlayed on the camera stream.

Figure 4
The overlayed emotion on the camera stream (own figure)

3.4 Created User Interface for the Web Server

To display the measured values, as well as the results and historical records, it was necessary to create a web application that will access the MariaDB database and display data from it in a user-friendly environment. The web server will run online on a hosting as well as the database.

The entire user interface consists of several pages; on which we have added several components to better understand the data. All of the components have their own use. To create the user interface, we have used Laravel, which is a free, open-source Symfony-based PHP web framework that allows developers to create web applications that follow the model–view–controller (MVC) architectural paradigm. We have used DataTables to display the data in the database for the user. DataTables is a jQuery plugin, which offers a large number of configurations to improve the ergonomics of viewing the data, especially when the data is large.

DateTime	Heart Rate
12/18/2021, 19:47:56	64
12/18/2021, 19:47:57	63
12/18/2021, 19:47:58	63
12/18/2021, 19:47:59	63
12/18/2021, 19:48:00	63

Figure 5
The data displayed in DataTables in the user interface (own figure)

The data in our user interface can be seen in the figure (Figure 5). By using the LavaCharts library, we can also visualize the data (Figure 6).

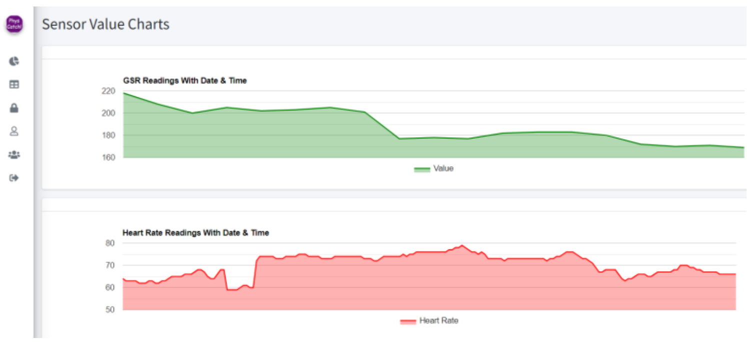

Figure 6
The data visualized in the user interface (own figure)

4 Results and Discussion

With the created system, an experiment can be carried out to gather physiological functions from users in real-time, while the video feed from the camera attached to the Raspberry Pi will be use in a classification algorithm, which will be able to classify basic emotional states based on the facial expressions of the user. The layout of the sensors can be seen in the figure (Figure 7).

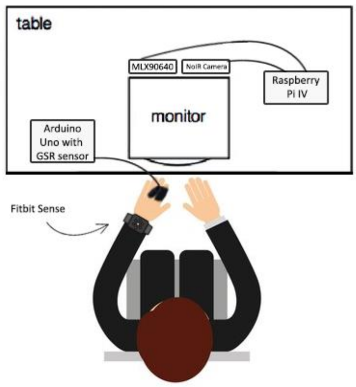

Figure 7
The layout of the sensors during the experiment (own figure)

During the experiment, we can show emotional movie clips to elicit emotions, which is a highly popular and effective method. Schaefer et. al. conducted a research, where they asked fifty film experts to name specific films that can elicit basic emotions. These film clips were then tested on 364 participants and a database of movies was created, which can be used in the context of emotional recognition [57].

In the experiment, the only invasive device is using is the GSR sensor, where the electrodes are attached to the finger of the user, however, in the future, it will be possible to measure glavanic skin response non-invasively as an electrodermal activity (EDA) ring is already being developed [58].

The main idea is to automatically gather physiological functions in real-time, while the sensor data is also sent to a database without any user input. At the same time, a facial recognition software is used to classify the emotions based on the facial expressions of the user. After a dataset is created, the measured physiological functions can be paired with the classified emotions based on the facial recognition software. In some cases, a delay in emotional stimulus must be calculated.

When studying the dataset, this strategy can also assist us in gaining indisciplinary knowledge:

– We can determine how much the measured physiological data reduced or increased for each user when they were experiencing specific emotions.
– We can determine how long the participants were in a neutral state and how long each emotion lasted during the experiment.
– We would not only be able to classify, but also predict emotional states. If we can assess physiological functions in real time and see changes in physiological functions that are typical of a certain emotional state, we may predict that the user will soon be in that emotional state. For example, if the GSR, HR, and body temperature levels gradually increase, the user is likely to experience fear or rage.

The dataset can later be used as an input to a machine learning algorithm, where the measured physiological functions would be the features and the emotion classified by the facial recognition tool will be the target attribute. The machine learning model will then try to predict the emotional state of the users only by using new measurements of physiological functions without using the facial recognition software.

Before using the created solutions on a larger number of participants in the academic environment, an alpha test has been carried out on five participants to test the created device. The physiological functions of User 1 is displayed in the following section. The user was monitored while he was browsing videos on social media.

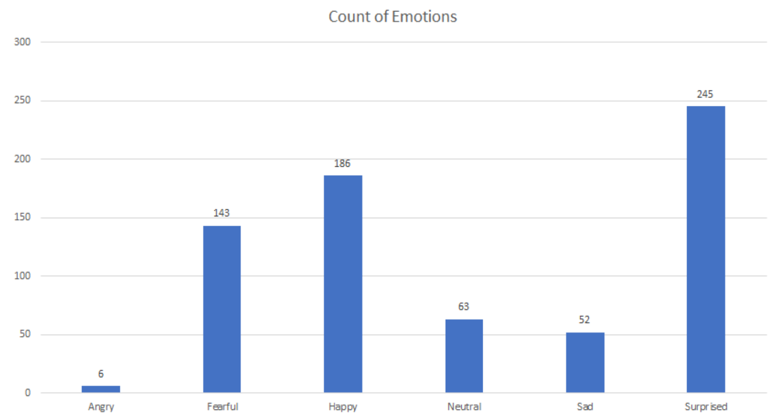

Figure 8
The count of emotions while the user was monitored (own figure)

According to the Figure 8, mostly he was surprised by the videos and the facial recognition software recognized the emotion of anger only six times. The user was not in the emotional state of disgust during the experiment.

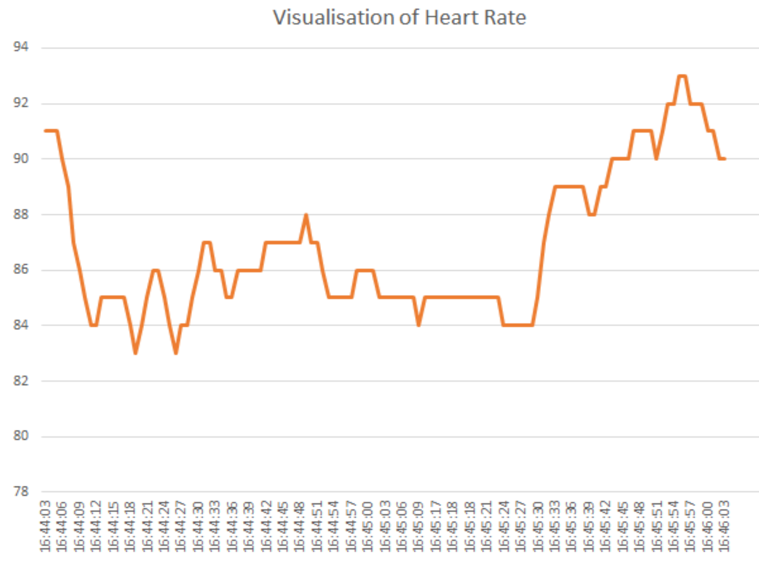

Figure 9
The visualisation of heart rate while the user was monitored (own figure)

The Figure 9 visualises the heart rate of the user during a short period time (2 minutes), while the user was being monitored.

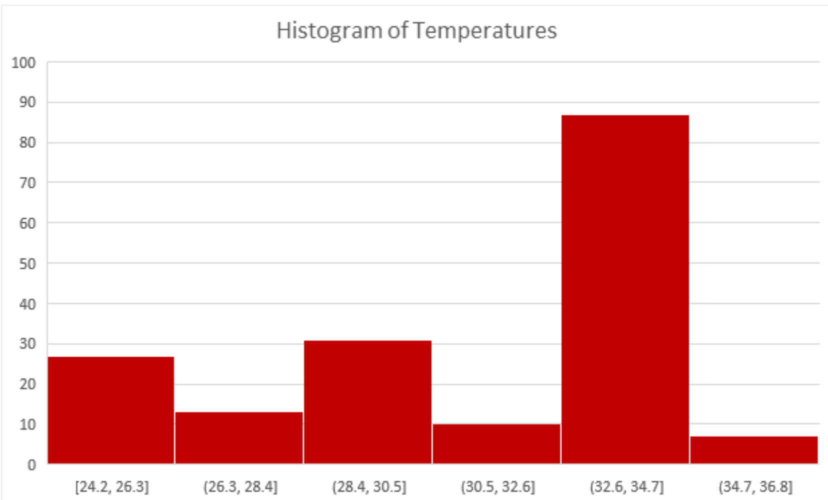

Figure 10
The visualisation of body temperature while the user was monitored (own figure)

Figure 10 shows the distribution of the surface temperature measurements of user 1's face. The temperature of the user's forehead was mostly between the values of

32.6 and 34.7C°. Extremely low values can be explained by the fact, that the user was moving during the experiment and the center point of the camera wasn´t detecting the user's forehead.

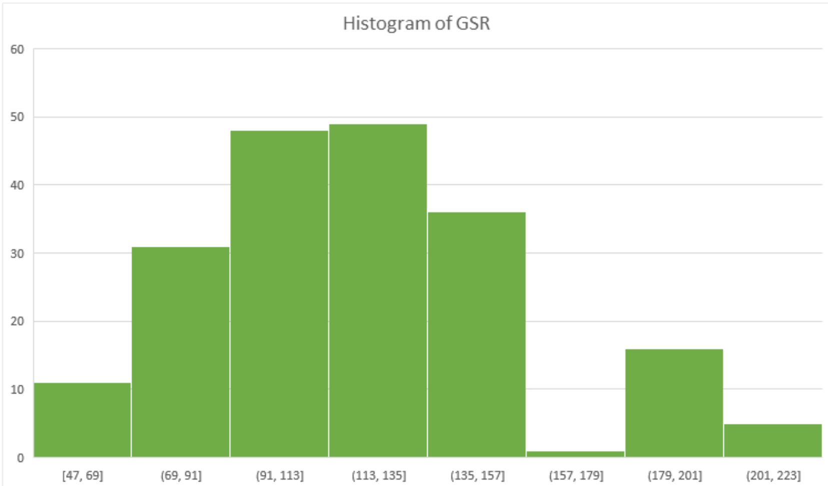

Figure 11

The visualisation of GSR while the user was monitored (own figure)

The user´s skin resistance is visualised in the Figure 11. Most measured values were between 113 and 135 ohms.

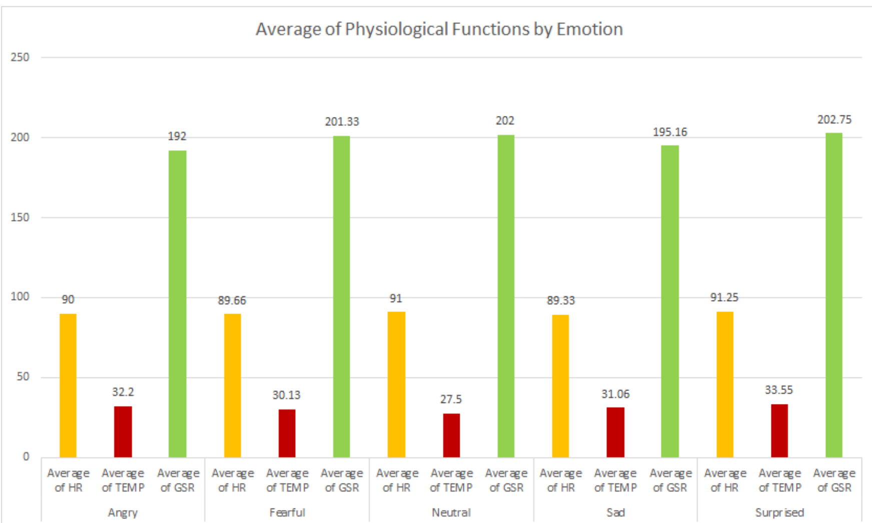

Figure 12

The average of physiological functions by emotions (own figure)

In Figure 12, it can be seen the average measurements of the physiological functions by emotions. Galvanic skin response was the highest while the user was surprised, while it was the lowest when he was angry. Average temperature was the lowest when the user was in neutral state and highest when he was surprised. Average heart rate was the lowest when the user was sad and highest when he was surprised. Results have shown that there are significant differences in the measured values for each emotion.

4.1 Usage of Results in Cognitive Infocommunications

Cognitive infocommunications investigate the relationship between several research areas such as cognitive sciences and infocommunications. Cognitive sciences often process inputs from psychology, computer science and artifical intelligence. An interdisciplinary field spanning computer science, psychology, and cognitive science is also affective computing. In the field of affective computing and human-computer interaction, the goal is to adapt intelligent systems to the emotional states of users.

The aim of the paper was to describe and create a sensory network to measure physiological functions. These physiological functions can be used in the field of machine learning to recognize the emotional state of the user. When the emotional state of the user is recognized, we can create softwares for a wide variety of devices to react to these emotions. For example, in smart homes, the users could define a set of actions by using their smartphones or web interface by using IF-THEN rules. One of the example rules can be that if they are afraid and its over 9 PM, the smart home should activate the alarm system.

4.2 Limitations and Future Directions

In this paper, we have presented the creation of an IoT device, with which we are able to classify the emotional states of a user. For the future there is a high demand for building a scalable, robust and efficient cost effective human emotion recognition systems. But in relation to these systems it is also worth noting that in some cases, it can also be difficult for people to accurately identify a facial expression, and different people may recognize different emotions in the same facial expression. This makes the classification difficult for the emotion recognition systems as well. The effective application of classification solutions requires a lot of training data. These data must contain images taken from different angles, with different backgrounds and the test subjects should be of different genders and nationalities. Improper pose, lighting, and changing contrast can cause problems when creating an image containing a facial expression prepared for image processing. The identification of facial expressions with lower intensity is more difficult and can be achieved with a much larger error. For this reason, in the future we will use only physiological data to recognize the emotions.

Conclusions

In this article, we described the existing methods and solutions for classifying the emotional state of a person, based on available IoT devices and we created a system that is able to measure the physiological signals of a person and determine the current emotional state of that person.

The physiological functions, such as HR, GSR and temperature highly correlate with emotional reactions. At the same time when these physiological reactions were measured, an emotion recognition software was also used that is able to classify emotions based on the facial features of the user. With these information, we can use supervised machine learning algorithms, where the measured physiological reactions are the features and the label is the emotion classified from the facial recognition tool. This way, the predict method of the selected machine learning algorithm will be able to recognize emotions by only using the measured physiological data without the need to use the facial recognition tool.

The device we designed can monitor a person's physiological signals, as well as evaluate their condition. The measured data is stored on a server in a MariaDB database. This device is simple to use, affordable and does not require a special environment to function properly.

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