International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
ISO 3297:2007 Certified ⋇ Impact Factor 7.047 ⋇ Vol. 10, Issue 8, August 2022
DOI: 10.17148/IJIREEICE.2022.10809

An IOT Based Smart Wearable System For Posture Management Using Machine Learning Technique

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Abstract: The utilization of skeleton information for human stance acknowledgment is a major examination theme in the human-computer collaboration field. This research proposes latest computation found various highlights and learning the rules to improve the precision of human stance. First and foremost, a 219-layer vector is defined, which includes point elements and distance highlights. The regular learning process combined with arbitrary subset techniques to produce a variety of tests and highlights for more refined sub-classifier classification execution for various cases during human stance categorization. Finally, four human stance datasets are used to assess the performance of our proposed technique. The results show that our algorithm can detect a spectrum of human positions and that findings acquired using a standard learning systems strategy are much more explicable than results conventional AI techniques and CNNs.

Keyword - IOT, SIFT, Pressure detection, Movements detection.

I.INTRODUCTION

Lately, the utilization of skeleton information for human stance acknowledgment has arisen as a famous exploration point in the realm of computer vision. This innovation manifest great possibilities in order to be used in human-computer communication, recovery medication, interactive media applications, augmented reality, robot control, and others. As a rule, stances are differ from activities in that the former is static while the latter is unique. A human stance provides a foundation for movement and is usually used as the primary criterion in various activity recognition calculations. Also, in some fields, for example, actual preparation, restoration preparing and communication via gestures correspondence, a human stance is a higher priority than an activity. Pose acknowledgment, as a human-PC connection mechanism, is far superior than keystroke control and spoken collaboration in noisy studios and dangerous work environments because it is more accurate, efficient, and consistent in cooperation. Pose recognition can be accomplished in a variety of ways. One is to utilize wearable sensors , like accelerometer and tension sensor. Nonetheless, wearing such a gadget understands trouble, which detracts the intuitive experience. The other one depends on monocular cameras. Be that as it may, it is defenseless to light and foundation impedance, offering unacceptable acknowledgment precision and vigoro in complex conditions. With the undeniably minimal expense profundity picture sensors, RGB-D picture based stance and activity acknowledgment has turned into a significant examination center in the field of human-PC cooperation. Specialists can get shading and profundity pictures just as Specialists can get shading and profundity pictures just as skeleton information of human without any problem. Many stance acknowledgment calculations that utilization skeleton information acquired from Kinect have been proposed. These calculations are immune to the effects of brightness, however they additionally dispose of the need of pre-processing, for example, division and item recognition in complex foundations, which empowers significantly further developed exactness. In any case, the majority of the current works are centered around the activity acknowledgment rather than the stance acknowledgment, with increasingly more consideration being paid to day by day activities. Furthermore, datasets and calculations in view of stance acknowledgment are still of restricted accessibility. Subsequently, in this research we offer a human stance acknowledgment technique that combines a few datasets with a large number of stances to achieve more precise stance acknowledgement. We segregate items at various granular levels and make assorted preparation subsets for increased precision in the standard based classifier, which is one of the study commitments. The classification step divides the initial preparation dataset into subgroups with separate tests and highlights using stowing and irregular subspace techniques. To cast a ballot, RIPPER classifiers prepared on these distinct preparation subsets are used to make the final

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selection.. For the current datasets, the trial results suggest that our calculation outperforms CNNs in any event, utilizing similar boundaries.

As of now, there are two sorts of human stance acknowledgment calculations: one depends on RGB picture and the other depends on profundity picture. The acknowledgment calculation in light of RGB picture utilizes the form highlights of human body, for example, the HOG highlights with all pieces of human body . In view of the profundity picture calculation, the dark worth of the picture is utilized to address the objective's spatial position and human shape, which can't be impacted by light, shading, shadow and attire. The above strategies have a decent impact for the body stances with standard activity, fixed point of view and position. Be that as it may, in actuality, stances fluctuate from one individual to another, and the position changes haphazardly not restricted to a solitary position. Hence, it is important to concentrate on a more general and adaptable human stance acknowledgment strategy. KinectV2.0 is taken on as stance securing gadget in this paper. The convolutional neural organization (CNN) was presented as the Posture-CNN model into pose identification to advance the preparation and handling of the stance attributes. The reasons for this trial are to tackle the current issues in the human body act acknowledgment, further develop the acknowledgment exactness, extend the extent of item benefits, and further develop the shrewd item administration framework.

II. EXISTING SYSTEM

Many examinations have been led to distinguish and address the stance discovery in the current framework. Numerous classifiers use sEMG signals, ANN, CNN, and SVM calculation to arrange sitting stance. The sitting stance is improved in a given plane by performing metric picture correction in every classifier, taking into account the extraction of straightforward and powerful highlights while as yet being helpful for continuous purposes. The vast majority of the customary stance acknowledgment strategies portray human visual data and two-layered stance data by separating highlights from RGB pictures. Ramanan and Sminchisescu [36] present a calculation which utilizes human shape tests to get human margin layouts and a similitude and angle plummet technique to assess stances. Jiang et al. [18] introduced a stance acknowledgment strategy utilizing curved programming based matching plans. This strategy ends up being more efficient than different techniques, for example, the chart cut or conviction spread techniques for the article coordinate with issue in huge looking through scale is intricated. However, these solutions are vulnerable to a few extraneous highlights like as people's clothing, climate impedance, and picture brightness.. Sarafanos et al. [37] looked examined the benefits and drawbacks of continuing research into three-dimensional human posture assessment. In comparison to the observed stance: the normal distance between 10 upper appendage joint locations and the point elements of 9 adjoining joints. The technique's recognition aftereffect is dependent on the matching limit being established, as a result, there isn't as much heartiness. In order to perceive yoga models for clients to describe human poses utilising the point between skeletal joints and to organise them. However, because it detects a huge number of similar attitudes, the approach only delivers limited precision. SVM was used by specific elements. Chen and Wang [6] proposed using the back proliferation (BP) organisation, SVM, and innocent Bayes as a method for seeing three poses. Instead of using component extraction, the original skeleton information is used as the classifier's information in this method.

III. PROPOSED SYSTEM

In the proposed System, discrete constant haptic input has been given and furthermore information on an individual gadget with respect to the stance of the wearer through convenient gadget. Using an accelerometer sensor to gather information on the location of the lower back and converting the raw quality from the sensors to exact lower back upsides. Then, at that point, the input can be sent through the vibration engine showing the client needs to address their stance. The motivation behind this framework is to coordinate stance location into a shrewd home climate to deliver a more vigorous mediation and security model to help each and every individual who works in the virtual world. This framework work for the most part depend on a nearby IOT organization to work. The proposed project means to foster a wearable checking framework that ceaselessly screens the client's stance utilizing an accelerometer, a power delicate resistor and EMG sensor. These sensors recognizes human stance framework and conveys the gathered information to a server through the web. Clients act is consistently observing to work on their inappropriate stance and to decrease spine wounds. It is fundamental for keeping up with great stance and a sound spine for taking on right sitting stance. Figure 1 depicts the several stages of this procedure.To begin, a variety of highlights were defined, including point highlights and joint distance highlights. Then, in light of the RIPPER rule learning calculation, packing and arbitrary subspace approaches were used to create rule gatherings, allowing for the development of 100 decision standard group for a larger percentage of those voting.

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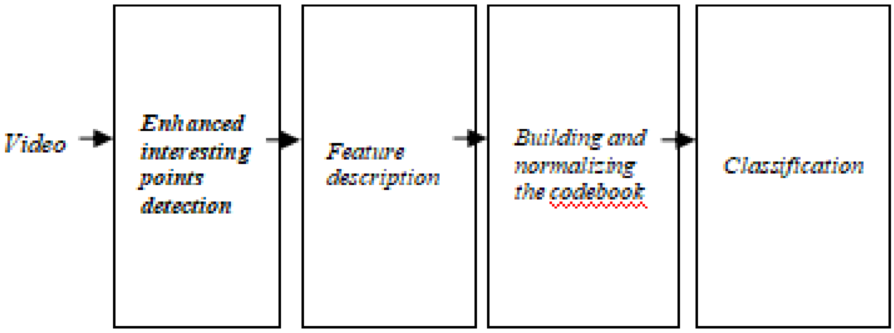

Figure 1 Overview of proposed software model

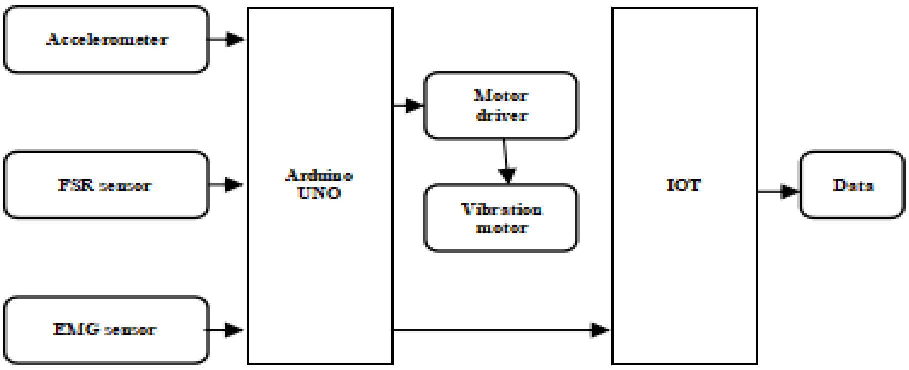

Figure 2. Block diagram of hardware interface

The sensor unit is in charge of interfacing with the wearer directly, measuring raw posture information and generating haptic input. The raw data is converted in the control unit into angles of the user's lower back to keep track of their posture. The vibration motor then sends feedback to the user, indicating that they need to improve their posture. Wireless tracking unit is used to monitor the sensors parameters wirelessly over the internet. Finally, the power unit is used to power the device. The power unit consists of Battery and Voltage Regulating circuits. It can provide blueprint for obtaining products and developing systems that IOT operate together to implement the overall system.

IV. DESIGN METHODOLOGY

The suggested framework is divided into four steps (as shown in Fig. 1): finding of interesting places, portrayal of recognized places, codebook construction, and characterization.

1. Enhanced interesting points detection

The interest focused discovering phase of the framework is where SIFT is used to conduct this interaction via calculation [17]. Tweaking the edge boundary is performed to change the quantity of interest focuses consequently as per how much subtlety in each casing. The adjusting is finished by at first apply limit esteem = 6 then, at that point, as indicated by the quantity of removed fascinating places (np) the edge (th) is set to another worth as follows:

If np>25 then th=14
else if np >20 then th=10
else if np>10 then th=8
else th=6

When limit esteem rise, substantial concentration focuses are identified, while the powerless concentration focuses are overlooked, when the limit esteem low, only the significant interest focuses are identified. This prevents the loss of important information. The improvement achieved by changing the limit is seen in Fig. 3. Clearly without utilizing a limit the quantity of extricated focuses is exceptionally high and they are unimportant where the vast majority of them lied behind the scenes. Using an edge, just the critical focuses are recognized without the requirement for an extra portion. SIFT's short element vector eliminates the requirement for techniques like pLSA and LDA for topic display,

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which require learning a distinct point model for each activity class and ordering fresh examples using the built-in activity theme prototype.

2.Image Labelling

K-implies groups the interest spots using the created descriptors; the resulting communities are known as visual words, and the arrangement of these words is known as jargon, resulting in a mark that is a histogram that indicates the recurrence of the terms in each video. For the KTH dataset, a comparison technique similar to Niebles et al. [13] is utilized, but only recordings of two entertainers are used to familiarize with the codebook because the entire amount of elements from all preparation models is too vast to use for grouping. The codebook size for the KTH dataset was determined to be between 900 and 1300. The impact of changing the size of the codebook on the precision of the results.

3. Classification

For characterization, here comes the SVM duty. SVM is a regulated learning model in AI that breaks down information and perceives designs using linked learning computations. The models are depicted as focuses in space in an SVM model. SVM maps a collection of prepared models, each of which is designated as having a position with one of the categories, so that the instances of the various classifications are separated by an acceptable hole that is about as big as can be predicted. During the testing phase, the preparation histograms are re-standardized alongside the testing histogram. The re-standardization procedure is carried out in such a way that each of the histograms has an impact on the final standardized test histogram (preparing ones and testing one). After that, the SVM is given the resultant standardized test histogram to characterize.

4. Hardware Interface

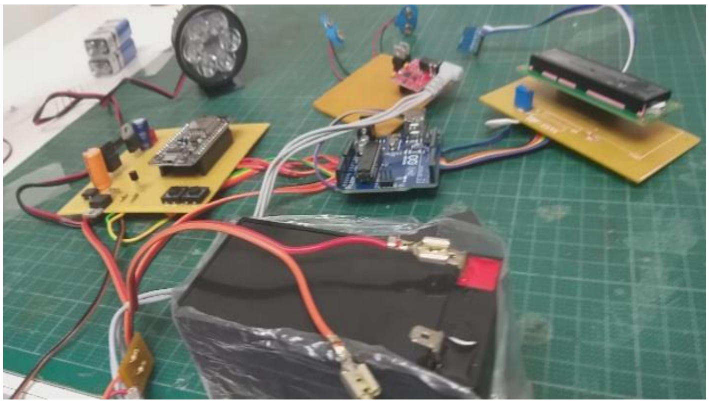

Figure 3. Hardware setup

The components used in this are 1.Arduino UNO 2. IOT 3. Accelerometer sensor 4.Force-sensitive Resistor (FSR) 5.EMG sensor 6.Light Dependent Resistor / Sensor (LDR) 7.Vibration Motor 8.Transistor BC547 9.LM7805 IC (5V) 10.Hi Watt (9V) 11.AH Sealed Lead Acid Battery 12.Liquid Crystal Display. It comes with firmware for Espressif's ESP8266-Wi-Fi SOC frameworks and equipment that relies on the ESP-12 module. It can speak with any microcontroller and make the undertakings remote. This is a Force touchy resistor with a square, 1.75x1.5"sensing region. FSR will fluctuate its opposition relying upon how much tension is being applied to the detecting region. The lower the blockage, the higher the power. When no stress is applied to the FSR, the obstruction will be more than 1 meter. A fluid precious stone is used to produce an apparent image on an LCD. Fluid precious stone presentations are ultra-thin revolutionary display displays seen in computers, televisions, mobile phones, and portable computer games.

ISSN (O) 2321-2004, ISSN (P) 2321-5526

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V. OUTPUT AND RESULTS

Figure 4. LCD Output

This above image in Fig.4 gives the output analog value from each sensors.

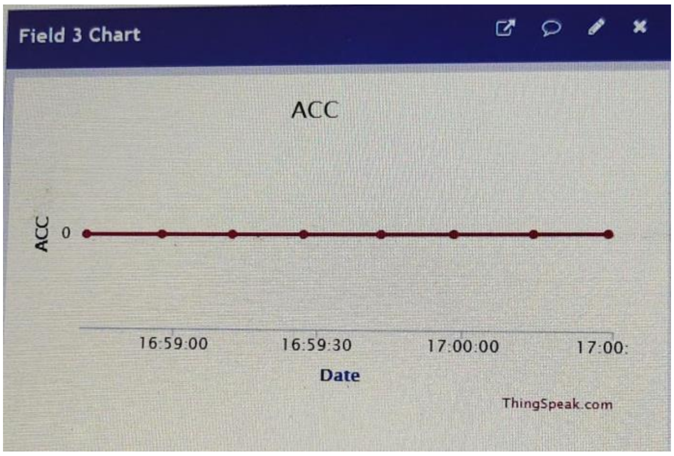

Figure 5. Accelerometer sensor output

This above image Fig.5 gives the cloud based IOT output of accelerometer sensor.

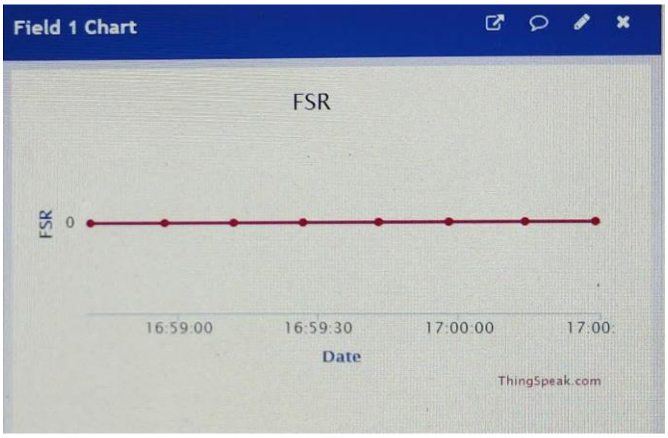

Figure 6. FSR sensor output

This above image Fig.6 gives the cloud based IOT output of FSR sensor.

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Figure 7. EMG sensor output

This above image Fig.7 gives the cloud based IOT output of EMG sensor.

Figure 8. Input Video

As of giving the input processing dataset as a video file in which a man is sitting.

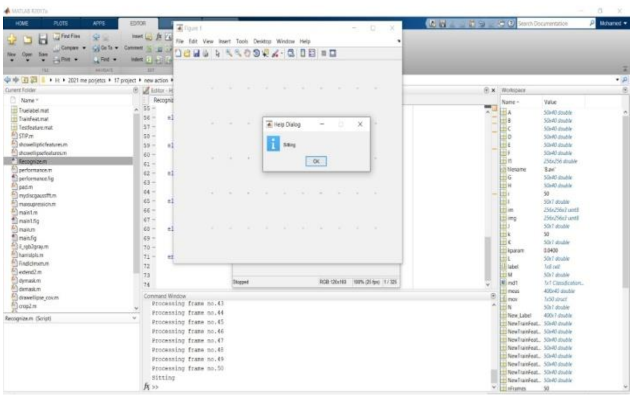

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Figure 9. Output Message box

This above image shows the output message of the given input where the image is processes and gives the output of the information in the video.

VI. CONCLUSION

This work presents a human activity acknowledgement framework that is quick and straightforward. The framework is made out of four phases: recognition of intriguing places, highlights portrayal, the pack of visual words, and grouping. On the daily basis, data will be transmitted on the cloud server. This system is proposed to use cloud server connected with sensor via Arduino UNO and IOT. The scenario has drawn a lot of researchers as a result of the pandemic, and numerous studies are underway to find best approach to detect human posture and provide better solutions. Using the sensors mentioned in this paper is a methodology that can be implemented to enhance the system's overall performance.

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