International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161
Available at http://inpressco.com/category/ijcet

Research Article

Development of an Intelligent Device capable of classifying Emotional Stress in correlation with Body Position

Anand Jatti[†], Madhvi Kannan[†], Alisha R Murugesh[†*], Shrestha Sinha[†], Vijayalakshmi P[†]

[†]Electronics and Instrumentation, R.V College of Engineering, Bangalore, India

Accepted 25 April 2016, Available online 30 April 2016, **Vol.6, No.2 (April 2016)**

Abstract

The main aim of this work is to develop a device that is intelligent in terms of progressively learning conditional changes that occur in the human body during times of distress and taking action if necessary. This paper delves into the concept of Machine learning for the classification of a subject's Emotional Stress Level and talks about the correlation of Emotional Stress with Activity Recognition. Additionally, it analyzes the significance of the correlation made. The paper deals with a device that has the capability of automatically perceiving any dangerous situation, and taking action if results prove to be positive i.e if subject is in danger. It does so by making use of an Open Source Machine Learning Toolkit- WEKA, which performs classification and evaluation of the data being recorded, thereby making the device intelligent. Analysis of all sensor data is done on MATLAB.

Keywords: *WEKA, MATLAB, Machine Learning*

1. Introduction

Physical assault is one of the most heinous crimes to be faced with. Research shows that physical assault takes place when an individual or a group provokes and attacks a person physically, with or without the use of a weapon, or threatens to hurt that person. Work-related aggression happens through the use of force or threats to a non-consenting victim on the work premises or in the context of the victim's work. An attempt to curb this issue was one of our major inspirations to develop this device.

The proposed device aims at automatically detecting any dangerous situation ie physical assault, rape etc. and sending an alert if victim has been subjected to attack. It does so by tapping two physiological parameters that change drastically during times of stress i.e Galvanic Skin Response and Finger Temperature. However, since the abovementioned parameters change during any normal physical activity (running, cycling etc), there was a need to look into a different aspect for the same device, in order to improve accuracy and make the device foolproof. Consequently, the concept of activity recognition was employed wherein the subject's physical activity at that particular instant was predicted in conjunction with their emotional state. This was done by making the device intelligent, i.e by making use of powerful machine learning algorithms for the precise classification of Emotional Stress and Activity Recognition.

*Correspondig author: **Alisha R Murugesh**

Devices and systems that deal with detecting emotional stress levels to predict danger and body position exist today, but they do so separately. A device called Suraksha (*Nishanth bharadwaj et al)* is directed towards safeguarding women and girls. It achieves this objective by providing a stress button/switch which when pressed sends out a distress signal. It also includes a voice recognition system and force sensing resistors that will send a distress signal when the device is thrown on the ground. The concept of using Galvanic Skin Resistance to ascertain levels of emotional stress is promising. Under stressful conditions the blood flow increases and the amount of electrolytes present on the surface of skin also increases thus increasing conductivity and decreasing the skin resistance (Azian Azamimi Abdullah *et al*, 2012). This proposed work draws focus towards combining physiological signals and Activity recognition.

Attempts have been made at recognizing user activity from accelerometer data (Lee & K.Mase 2002; Bussmann *et al*. 2001). The most exhaustive work in this regard is that of Bao & Intille (2004). In their experiments, subjects wore 5 biaxial accelerometers on different body parts as they performed a variety of activities like walking, sitting, standing still, watching TV, running, bicycling, eating, reading etc. Data generated by the accelerometers was used to train a set of classifiers, which included decision trees (C4.5), decision tables, naive Bayes classifier and nearest-neighbor algorithm found in the Weka Machine

Learning Toolkit (Witten & Frank 1999). Decision tree classifiers showed the best performance, recognizing activities with an overall accuracy of 84%. In this work we have attempted to recognize activities using a single triaxial accelerometer worn on the hand. Activity recognition is formulated as a classification problem. In addition to analyzing the performance of base-level classifiers (Bao & Intille 2004), we have studied the effectiveness of meta-level classifiers (such as boosting (Freund & Schapire 1996), bagging in improving activity recognition accuracy.

We have tried to answer the following questions with regard to activity recognition (1) Which are the best classifiers for recognizing activities? (2) Which among the selected features/attributes are less important than others?

2. Problem Definition

To design and develop a device that has the ability to progressively learn conditional changes that occur within the human body during times of distress and correlate it with body position. The concepts used to achieve this objective are Physiological sensor data and Activity recognition working in conjunction. The following questions are answered in the subsequent paragraphs:

1. How is Activity Recognition performed?
2. How does Activity and physiological sensor signals correlate?
3. How does integrating activity recognition and physiological sensors improve the performance of the proposed device?

3. Methodology

- The first step in developing this device is to acquire sensor data. The sensors used for this purpose are temperature sensor, triple axis accelerometer and skin resistance sensor
- The next step is sending sensor data to an Open Source Cloud Platform, ThingSpeak via the ESP8266 Wi-Fi module.
- Final step, is retrieval of sensor data from Cloud onto MATLAB for further analysis.

3.1 Feature Extraction

3.1.1 Physiological Sensor Data Feature Extraction

The physiological sensor data used in this device are-Skin Resistance and Finger Temperature.

During times of distress, skin resistance and finger temperature undergo drastic decrease from nominal value. However, this nominal value varies from person to person, as a result of which, learning has to be incorporated into the device being used.

The first step in learning is extracting features. Since there is a drastic decrease in skin resistance and finger temperature during times of distress, it was found to be most suitable to compute the difference between the two values of each parameter for stressed and relaxed states as features.

Step 1: Continuously read skin resistance and temperature sensor data and store into an array for both stressed and relaxed states

Format : {Skin_difference, Temp_difference, Class (Stressed/Relaxed)}

Formatting is done in .ARFF file format as the usage of WEKA(Open Source Machine Learning Toolkit) requires data to be classified into .arff file formats.

3.1.2 Activity Recognition Feature Extraction

For the purpose of activity recognition, a triple axis accelerometer has been used in order to obtain the X,Y and Z axis data. This data that is being recorded in Cloud is retrieved for analysis in MATLAB. Activity recognition is done for 4 positions- sitting, standing, sleeping and struggle.

First step in analysis is precise filtering of data. Since the X,Y and Z axis data are raw, they need to be filtered before being processed. The method of filtering used is an Exponential Moving Average Filter, which is a first order low pass digital filter.

Next step of analysis is to compute features, as in the previous case. The following features are computed – average of X,Y and Z axis, Standard deviation of the 3 axis, correlation of XY,YX and XZ axis, average of the magnitude of the 3 axis, and standard deviation of the same,, and energy

Step 1: Firstly, 500 samples of X,Y and Z axis data are recorded. These 500 samples are broken into blocks of 64 samples each and the abovementioned features are computed for each block

Step 2: These features are then stored in a training. Arff file like in the previous case

Format : {{avgx,avgy,avgz,stdx,stdy,stdz,Corrxy,Corryz,Corrzx,avgAcc,stdACC,Enerygy, Class(Sitting/Standing/Sleeping/Struggle)}

3.2 Choosing a classifier

Activity Recognition

Table 1: The above table shows the results of the accuracy of the various classifiers that were tested

Classifier	Sitting	Standing	Sleeping	Struggling
Naiive Bayes (NB)	53.8	27.9	31.6	73.2
Bagged NB	77.8	36.4	30.8	75.7
Multilayer perceptron(MP)	70.7	65.4	92.3	96.2
Bagged MP	84.2	70	98	91.7
Breadth first tree (BF)	88.6	82.7	97.7	92.3
Bagged BF tree	94.4	92	100	92.2
Decision table (DT)	71.4	57	100	79.2
Boosted DT	81.4	92.9	100	94.1
Bagged DT	96.3	78.9	100	83.9
Decision tree (DTr)	92.3	85.2	100	100
Bagged DTr	94.7	91.8	97.8	95.9
J48 Graft	92.3	85.2	100	100
Bagged J48 Graft	94.4	91.8	97.8	92.2

The system should be able to recognize the activity based on the accelerometer signals. By observing the x,y,z patterns it is evident that the signal patterns are different for different activities. Hence in this work activity recognition is regarded as a classification problem where the classes are sitting, standing, sleeping and struggle and the test instances are the accelerometer data after feature extraction. We evaluated the performance of the following classifiers:

- Naiive Bayes
- Multilayer Perceptron
- Breadth-first tree
- Decision table
- Decision tree
- J48 graft

The result of the analysis is displayed below:

Classification into stressed/relaxed using physiological sensors and learning algorithms

A similar accuracy test as performed for activity recognition was performed for the sensor data to classify it into stressed and relaxed conditions. Analysis showed that SimpleLogistic was the most accurate classifier for this purpose.

3.3 Feature Selection

Further, while performing machine learning it must be kept in mind that there are some features that contribute towards improving the accuracy of the system and there are some that might have a negative impact on the performance accuracy. To this effect, using the WEKA tool analysis was performed to select only those features that have a positive impact on the system's performance

The results of the analysis are displayed below:

Table 2: Feature selection analysis performed to identify features that have a positive impact on system accuracy. Only those classifiers with higher accuracies (highlighted in table 1) are chosen for feature selection analysis

CLASSIFIER	AvgX	AvgY	AvgZ	stdX	stdY	stdZ	CorrXY	CorrYZ	CorrZX	avgAcc	stdAcc	energy
BF tree	✓			✓	✓				✓	✓		✓
Bagged BF tree		✓	✓	✓	✓			✓	✓	✓		
Boosted Bf tree	✓	✓										
Boosted Dtable	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓
Bagged Dtable	✓	✓	✓			✓			✓		✓	
Decision Tree	✓		✓	✓						✓		
Boosted DTR	✓		✓									
Bagged DTR	✓	✓	✓					✓	✓	✓		
J48 Graft	✓		✓	✓						✓		
Boosted J48 graft	✓	✓										
Bagged J48 graft	✓	✓	✓	✓				✓				

3.4 Building model and Evaluation of trained model against test data

3.4.1 Building training models

Next step, is to build the training model for each of the 2 training files generated. This is done by first calling the /weka.jar library in MATLAB. The shortlisted classifiers for each of the two sets of data are then used for classification.

Boosted J48 is used for training the file concerned with activity recognition and SimpleLogistic is used for training file concerned with classification of emotional stress.

Classification results in model being built that is ready for evaluation. Simultaneously, a test file(.arff file format) is created for each of the training models that are built.

3.4.1 Evaluation of trained models against test data

Next step is the evaluation of trained models against test data. The test data is being fetched continuously on MATLAB, from ThingSpeak (Cloud Platform). Features of the Physiological sensor data and accelerometer data have to be fed into their respective test files. Evaluation takes place between the trained model and the appended test data(test.arff file) for each of the two models. Predictions are given based on the evaluation and recorded.

4. Results and discussion

Classifier accuracy and feature selection experiments showed that for Activity recognition the Bagged J48Graft has the highest accuracy. Average of X, Y and Z along with Correlation between Y and Z axes were the features that were found to be the most contributive features in the classification of accelerometer data using Bagged J48 Graft Algorithm.

In order to test this system, it was required to gather test subjects and subject them to stressful circumstances such that their body would react as it would during a real-life stressful situation.

For this purpose Stroop word colour test was incorporated.

It is based on Stroop effects. In psychology, Stroop effect is said to be the demonstration of interference in reaction time of a task. Here the subjects are voluntarily put under stress when the name of a color is printed in a color not denoted by the name. Under such cases, naming the color by subjects would take more time and also the subjects are prone to more errors which automatically increase the stress level. After collecting data a model was built and its accuracy verified.

```
Kappa statistic                          1
Mean absolute error                      0.1192
Root mean squared error                  0.1192
Relative absolute error                 23.8453 %
Root relative squared error             23.8476 %
Coverage of cases (0.95 level)         100      %
Mean rel. region size (0.95 level)     100      %
Total Number of Instances               20

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC
                 1.000    0.000    1.000      1.000    1.000      1.000
                 1.000    0.000    1.000      1.000    1.000      1.000
Weighted Avg.    1.000    0.000    1.000      1.000    1.000      1.000

=== Confusion Matrix ===

  a  b   <-- classified as
 10  0 |  a = Stressed
  0 10 |  b = Relaxed
```

Figure 1 As it can be seen in the figure above after choosing the classifier analysis a 100% accuracy in classifying into stressed/relaxed was achieved

To verify the accuracy of the Activity recognition, subjects were instructed to wear the device on their hand and then perform sitting, standing, sleeping and struggling (vigorously shaking) exercises. The collected data was then used to test the accuracy of the activity recognition algorithm.

```
Root relative squared error              0.0113 %
Coverage of cases (0.95 level)         100      %
Mean rel. region size (0.95 level)      25      %
Total Number of Instances              363

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC
                 1.000    0.000    1.000      1.000    1.000      1.000
                 1.000    0.000    1.000      1.000    1.000      1.000
                 1.000    0.000    1.000      1.000    1.000      1.000
                 1.000    0.000    1.000      1.000    1.000      1.000
Weighted Avg.    1.000    0.000    1.000      1.000    1.000      1.000

=== Confusion Matrix ===

   a   b   c   d   <-- classified as
 146   0   0   0 |   a = sitting
   0  70   0   0 |   b = standing
   0   0  77   0 |   c = sleeping
   0   0   0  70 |   d = struggle
```

Figure 2 As it can be seen in the figure above after choosing the classifier and features as per analysis a 100% accuracy in activity recognition was achieved

In this work both the above algorithms work in conjunction to achieve the objective of this work. If the prediction results in a situation where the algorithms predict a stressed-struggle instance then it is concluded that the subject is in a dangerous situation and the designated individual is notified.

Conclusion

This work attempts to tackle a societal concern that has been destroying the lives of uncountable individuals and their families. This device continuously monitors the individual wearing it, the data being accessible world over enabled by the benefits of cloud computing. The data can thus be downloaded onto any remote station for monitoring and analysis. The machine learning algorithms used make the device intelligent and the accuracy of which increases with continued use.

A device like this improves the level of safety of women and girls. Accurate recognition of a dangerous situation is a complex matter, however, the scope for improved accuracy is promising.

Future Scope

For a system such as the one developed in this project only the sky is the limit with regards to its future potential and further advancements. Following are a few different paths that can be followed to improve the system developed in this project .

- Thingspeak is an already established cloud server which has a property of reading continuous sensor data only once every 16 seconds. This is done to attain stability. However, 16 seconds delays the entire process of real-time monitoring by a large amount, and therefore, as a future scope, a dedicated cloud server for the purpose of monitoring sensor data specific to this particular application has to be developed.
- ESP8266 wifi module, makes use of the concept of latching onto the nearest network, thereby providing internet. As for this application, the necessity to have a well established network in every area is absolutely crucial in determining the victim's conditions.

References

Nishkam Ravi, Nikhil Dandekar, Preetham Mysore and Micheal L. Littman (2012), Activity Recognition from Accelerometer Data, Department of Computer Science, Rutgers University, Piscataway

Jorn Bakker, Mykola Pechenizkiy, and Natalia Sidorova (December 11, 2011), What's your current Stress Level-Detection of Stress patterns from GSR sensor data, 11th IEEE International Conference on Data Mining Workshops, Eindhoven University of Technology, The Netherlands, 978-0-7695-4409-0/1 pp 573-580

V.J. Madhuri, R. Madhumitha Mohan, R. Kaavya, Stress Management Using Artificial Intelligence, Third International Conference on Advances in Computers and Communication, Sri Perumbudur, Tamil nadu

María Viqueira Villarejo, Begoña García Zapirain, and Amaia Méndez Zorrilla (2012) , A Stress Sensor Based on Galvanic Skin Response (GSR) Controlled by ZigBee, DeustoTech-

Life Unit, Deusto Institute of Technology, University of Deusto, Avda. de las Universidades, Spain, pp. 6075-6101

Bussmann, J.; Martens, W.; Tulen, J.; Schasfoort, F.; van den Bergemons, H.; and H.J.Sta (2001) Measuring daily behavior using ambulatory accelerometry: the activity monitor. Behavior Research Methods, Instruments, and Computers 349–356

Bao, L., and Intille, S. S. Activity recognition from user-annotated acceleration data. In Proceceedings of the 2nd Interna- tional Conference on Pervasive Computing, 1–17(2004)

Freund, Y., and Schapire, R. E. (1996) Experiments with a new boosting algorithm. In International Conference on Machine Learning, 148–156 Lee, S., and K.Mase.. Activity and location recognition using wearable sensors. IEEE Pervasive Computing 24–32.(2002

Witten, I., and Frank (1999), E. Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations. Mor- gan Kauffman