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Gyroscope Explorer Terrain Angles Classification

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Abstract

Mobile Applications (Apps) offer numerous advantages related to entertainment, communication, monitoring and sensing to name a few. In this study, a Gyroscope Explorer Apps is employed for data gathering of azimuth, pitch, and roll. The mobile phone is carried by Lego Mindstorms (EV3), in which it travels the ladder into the different angles: 4.13°, 7.77°, 10.81°, and 12.80°. The data collected was classified into eight classes: 4.13°uphill, 4.13°downhill, 7.77° uphill, 7.77° downhill, 10.81° uphill, 10.81°downhill, 12.80° uphill, 12.80° downhill. Artificial Neural Network is used to classify the angels and the orientation of the vehicle-uphill or downhill. A total of 718 data collected and divided into three sets (azimuth, pitch and roll). The number of neurons in the hidden layer is set to 10, yielding a 100% accuracy classification.

1. Introduction

Smartphone and tablet devices installed with Apps perform supplementary functions connected to telecommunication, health, sports and entertainments enabling a cost-efficient sensor and improved decision-making in various applications. Apps are software applications which can be downloaded into smartphones, tablets, and e-readers to provide solutions for niche requirement. One of the most common is medical apps. It has an enormous potential for improving clinical practice by providing a quick, comprehensive, and up to date overview of current clinical guidelines, making a differential diagnosis, and performing useful calculations [1]. Medical and lifestyle apps provide a valuable way of sharing information, working more efficiently and supporting diagnosis, treatment, and patient outcomes. Mobile medical apps can pose the same risks of failure as other medical devices, including mechanical failure, faulty design, poor manufacturing quality, and user error, among other safety issues [2]. The widespread use of mobile technologies has the potential to provide new and innovative ways to improve healthcare, entertainment, and quality of life of the human being. Clinicians have increasingly embraced the use of both smartphones and tablets in their professional capacity over the past few years. A survey conducted by GMC demonstrated that in 2011, 30 % of doctors used a smartphone Apps [3]. According to [3], in 2012, 83% of medical doctors would use smartphones in their work.

2. Apps add functionality on Mobile phone

There are many Apps that could be used in the medical realm. These include calorie meter, altimeter, heart and oxygen apps, etc. Apps could also be utilized in the field of sports science such as monitoring the altitude. According to some studies the altitude has profound effects on exercise and athletic performance. Having information about hypobaric hypoxia induced by increasing terrestrial altitude is vital in determining its effects on human. This has major physiological physical effects, both of which will influence football performance.VO2max is a measure of the maximum volume of oxygen that an athlete can consume. It is measured in milliliters per kilogram of body weight per minute (ml/kg/min). According to Levine and Stray- Gundersen [4], VO2max at altitude beginning as low as 800m altitude and extending through 2800m with a decline rate of 6.3% per 1000m altitude-range 4.6– 7.5%/1000m. Measuring this type of data could enhance human performance in conducting different activities.

Apps for heart rate is also widely used. This provides vital information in monitoring the heart rate of the user. It could compare his/her heart rate with that of a normal one when performing activities. An important consideration is the mountaineers. The average percentages of heart rate reserve for the downhill section (131.4 beats/minute) and the uphill section (167.8 beats/minute) were 54% and 81%, respectively. Downhill heart rates are within moderate intensity levels, 40% to 60% of heart rate reserve and uphill heart rates are within vigorous intensity levels greater than 60 % of heart rate reserve [5].

Mobile phone Apps enable the control of electronics equipment and vehicles. A variety of wheelchair products and services are changing rapidly. Among them is a handicapped assistive wheelchair product in conjunction with smart mobile. A lot of research including but not limited to voice recognition, gesture, iris recognition and wheelchair movement has been done [7][8][9]. A wheelchair is developed to maintain equilibrium of a seat in conjunction with the smart mobile device. Using smart mobile devices to control the wheelchair seat and using the seat control system was to prevent the bedsores [8]. In addition, other smart mobile devices used “cloud” [10] for the same personalized service.

Significant research on intelligent wheelchairs has focused on the design and control aspects, including but not limited to human-machine interfaces and autonomous navigation [11] – [16]. From the accelerometer attached on the board of smart wheelchairs the activities of the user could be characterized [17].

The practice of apps with mobile has merged into diverse functionality and develop more possibilities in technology.

This study aims to employ Gyroscope Explorer Apps that could be installed on a mobile phone with Android operating system. And to also gather data in terms of azimuth, pitch, and roll from different angles of elevation-uphill and downhill. Artificial Neural Network is performed in classifying the angles based on the measured azimuth, pitch, and roll. The study aims also to achieve a high accuracy and classification of the different angles using Gyroscope Explorer Apps. The ability of the Apps to classify the different angles or terrain with high accuracy is pf paramount importance to control motors and other electronic devices. This could be used to perform various activities that improve human life in terms of support, error correction, and intelligent control systems.

3. Methodology of the study

The complete process of this study is shown in Fig.1. The first block is for data acquisition in which a Gyroscope Explorer was used. Gyroscopes measure the rotation of a device with a pair of vibrating arms that take advantage of what is known as the Coriolis-Effect caused by Earth rotation. It measures the changes in the direction of the vibrating arms, and an estimation of the rotation is then produced. This app is installed in a Mobile phone, which serves as the gyroscope sensor and data logging device.

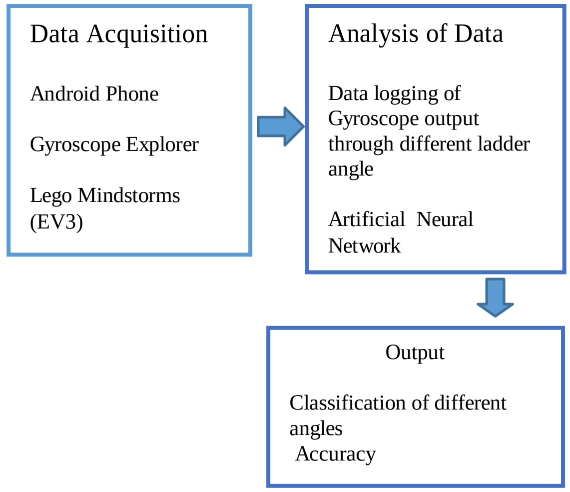

Fig. 1. Data Acquisition and Analysis Processes.

The mobile phone was placed on top of the Lego Mindstorms (EV3) and it traveled the ladder from its lowest tip point to its highest point (uphill) at a time, then, repeated with different angles of elevation. The same process was carried out in the downhill direction. In order to measure the azimuth, pitch, and roll of the moving vehicle (EV3), the Gyroscope explorer was employed. It is installed in the mobile phone, and data logging is utilized for each angle of elevation. Fig. 2 shows the Lego Mindstorms (EV3) used to carry the mobile phone. It is operated by remote controller called robot commander (App), installed in another mobile phone. Fig. 3 shows how the Lego Mindstorms (EV3) was used to travel the ladder into different angle: 4.13°, 7.77°, 10.81°, 12.80°. The data collected was categorized into eight classes: 4.13°uphill, 4.13°downhill, 7.77° uphill, 7.77° downhill, 10.81° uphill, 10.81°downhill, 12.80° uphill, 12.80° downhill. One of the limitations of this study is the slight timestamp difference in other sample data which is due to the manual start and stop recording. Also, the total numbers of generation of the point have slight variance with other samples recorded data.

Fig.2. Lego Mindstorms EV3[19]

Fig.3. Data logging from Gyroscope Explorer

Artificial Neural Network was implemented using Matlab *nprtool* code. It is neural pattern recognition (App). The neural network of Matlab is a two-layer feed-forward network, with *sigmoid* hidden and *softmax* output neurons which can classify vectors arbitrarily well, given enough neurons in its hidden layer. The network is trained with scaled conjugate gradient back propagation. The data recorded from the mobile apps are in CSV (comma separated values) files. There are 718 generations, leading to an equal number of (azimuth, pitch, and roll) sets. The data is divided into three sets: training, validation, and testing.

- Training set: These are presented to the network during training, and the network is adjusted according to its error.
- Generation: These are used to measure network generalization, and to halt training when generalization stops improving.
- Testing: These have no effect on training and so provide an independent measure of network performance during and after training.

4. Data and results

Sample data logged by Gyroscope Explorer is shown in Table 1. This data were gathered wherein the vehicle traveled the ladder with an angle of 4.13° at a downhill direction. The actual number of data sets generated is composed of a total of 69 sets of azimuth, pitch, and roll.

Table 1. Sample data acquired from Gyroscope Explorer

Generation	Timestamp	Azimuth	Pitch	Roll
0	0	-1.792	-0.064	0.0141
1	0	-1.793	-0.064	0.0127
2	0.11	-1.792	-0.063	0.013
3	0.21	-1.792	-0.063	0.0125
4	0.31	-1.792	-0.063	0.0126
5	0.41	-1.792	-0.063	0.0125
6	0.51	-1.792	-0.063	0.0125
7	0.61	-1.792	-0.063	0.0124
8	0.71	-1.792	-0.063	0.0123
9	0.81	-1.792	-0.063	0.0122
10	0.91	-1.792	-0.063	0.0121

The results of the Artificial Neural Network Classification were carried by setting 70% of the data under the training set, 15% of the data was on the validation set, and 15% of the data was on the testing set. MatLab performed the random division of the 718 into these three sets. The number of hidden neurons in the hidden layer was set to 10. The more neurons, the better is the classification. There was no need to increase the number of hidden neurons because the classification has 100% accuracy. Fig.4 shows the best validation performance is 3.2892e-06 at epoch 160. The yellow line represents the Train, the green line represents the validation and the red line represents the Test and the dotted line represents the Best. Fig. 5 shows the snapshots of the results of training the neural network. Generally, the error reduces after more epochs of training but might start to increase on the validation data set as the network starts overfitting the training data. The best performance is taken from the epoch with the lowest validation error[20].

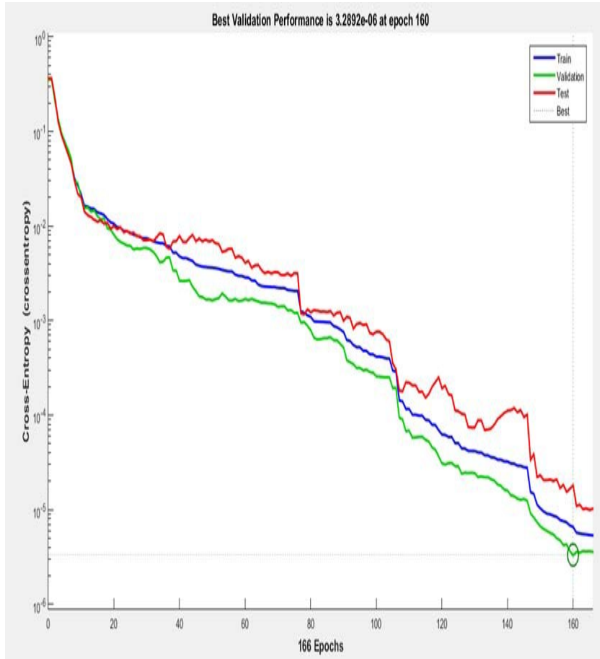

Fig. 4. Best validation performance

It shows that Minimizing Cross-Entropy results in good classification. Lower values are better. Zero means no error. Percent Error indicates the fraction of samples which are misclassified. A value of 0 means no misclassifications, 100 indicates maximum misclassifications. The %E column, the training, validation and testing sets resulted in zero percent error or misclassification.

Results

	Samples	CE	%E
Training:	502	5.94803e-0	0
Validation:	108	16.63164e-0	0
Testing:	108	16.66807e-0	0

Fig. 5. Artificial Neural Network results

Fig. 6 and 7 show the training, test, and validate, all ROC. The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test. The closer the curve comes to the 45- degree diagonal of the ROC space, the less accurate the test [21].

The colored lines in each axis represent the ROC curves. The ROC curve is a plot of the true positive rate (sensitivity) versus the false positive rate (1 - specificity) as the threshold is varied. A perfect test would show points in the upper-left corner, with 100% sensitivity and 100% specificity.

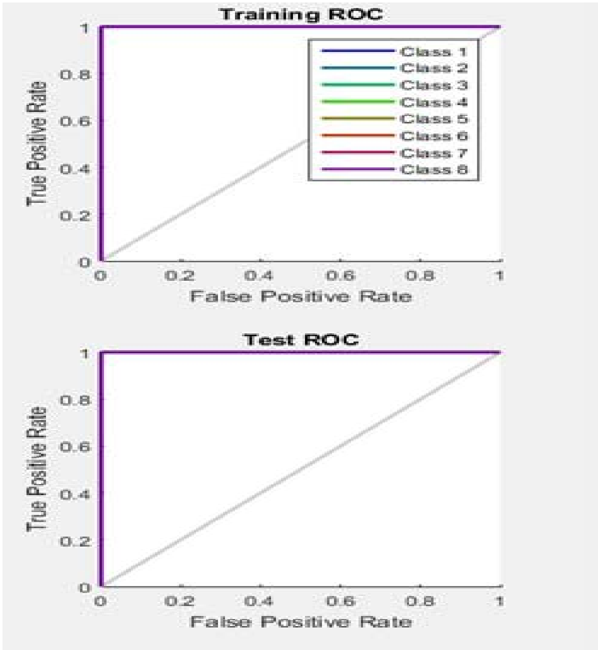

Fig.6. Training ROC and Test ROC

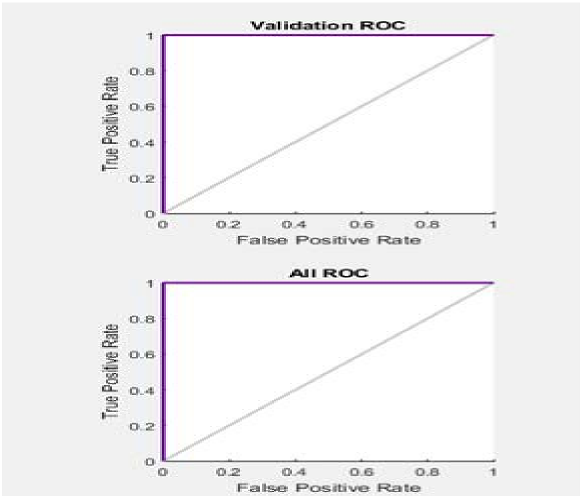

Fig. 7. Validate Roc and All ROC

5. Conclusion

The used of mobile apps is successfully developed in this study. Furthermore, mobile phones and apps could introduce another function that performs a specific task. Gyroscope Explorer Apps and Android Mobile were used to gather different sets of data at different angles. These angles are classified into eight namely: 4.13°uphill, 4.13°downhill, 7.77° uphill, 7.77° downhill, 10.81° uphill, 10.81° downhill, 12.80° uphill, 12.80° downhill. There are 718 data into the three sets (pitch, roll, azimuth) generated for the classification. Artificial Neural Network was used for the classifications. The number of hidden neurons in the hidden layer is set to 10, which yields to the classification of 100% accuracy. This study suggests that Gyroscope Explorer apps is capable of providing the needed data in order to classify the angle of elevation of the terrain in which the mobile phone is located. Accurate classification provides a better application in the regulatory a control systems for robotics and vehicles. This capability breeds to a self- learning devices and various applications in the industrial operations.

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