HEAD MOTION RECOGNITION USING A SMART HELMET FOR MOTORCYCLE RIDERS

K.I. WONG[1], YI-CHUNG CHEN[2], TZU-CHANG LEE[3], SHENG-MIN WANG[4]

[1] Department of Transportation and Logistics Management, National Chiao Tung University, Taiwan
[2]Department of Industrial Engineering and Management, National Yunlin University of Science and Technology, Taiwan
[3]Department of Urban Planning, National Cheng Kung University, Taiwan
[4]Department of Information Engineering and Computer Science, Feng Chia University, Taiwan
E-MAIL: kiwong@mail.nctu.edu.tw, mitsukoshi901@gmail.com, jtclee@mail.ncku.edu.tw, spc023151@gmail.com

Abstract:

This paper presents a head motion detection and recognition study using a smart helmet for motorcycle rider which can potential be used for the analysis of behavior of motorcycle riders. The smart helmet is a full face motorcycle helmet integrated with an intelligent system embedded an Inertial Measurement Unit (IMU) sensor. In the analysis, the motions and the corresponding signals are assessed with the video footage with a data acquisition and visualization platform. We introduce a feature extraction methodology to extract the most discriminant features from the signal data, and the head motion recognition problem is formulated as a machine-learning based classification model. Experiment results show that gyroscope sensor data is more useful than accelerometer sensor data for head motion recognition and the classification accuracy for different head motions ranges from 95.9% to 99.1%.

Keywords:

Tracking; Activity classification; Head motion; IMUs; Motorcycle; Smart helmet; Wearable sensors

1. Introduction

Driving analytics is an emerging area that sensing devices and vehicular technologies are used in the study of behaviors of drivers. Wearable sensors and mobile technologies can be useful in providing data for the monitoring of human activity, actions and gestures. The information can support the understanding of how the rider interacts with the traffic environment and the identification of extreme driving patterns. Wearable sensors such as Inertial Measurement Unit (IMU) have been widely used for the study of human activities [1-4].

An amount of research is undergoing in the development of smart helmets integrated with sensors in measuring the head motions, fatigue, and physiological conditions of the wearer [5-7]. Recognizing the gestures, irregular motion, level of attention, and the environment can help in predicting the risk of accidents and potentially improve their safety.

Smartphones embedded with various kind of sensors including GPS and Inertial Measurement Unit (IMU) can provide data on actual driving in a non-intrusive environment. Critical driving patterns such as harsh acceleration, braking and turning can be detected with the sensor systems to analyze the driving style of drivers [8-10]. Similarly, the orientation, amplitude and frequency of a rider's head turning could be possibly an indicator for the level of focus or being distracted by roadside objects. A smart helmet reporting measurements of head motions and gestures of riders can be used to support naturalistic studies and riding behavior analytics. A challenge of recognizing head motion is that the sensors provide measurements under a noisy environment. There are noise in the readings due to head and body movements, and algorithms are developed to eliminate the errors and estimate the motions such as by extended Kalman filter algorithm [6, 11].

In this study, to recognize head motion activities of motorcycle riders under riding conditions, we develop an activity classification methodology for smart helmet. An Inertial Measurement Unit (IMU) sensor is used to estimate the head movements and videos from the embedded camera are used for labeling of activities and incidents of interest. Four riding and head motion patterns are included in this study: Looking Up, Looking Down, Turning Left and Turning Right. Experiments with participants wearing the helmet and riding a motorcycle are conducted to evaluate the performance of the proposed methodology.

The riding pattern recognition problem is formulated as a classification problem to identify the riding pattern from the measurement. The first step is pre-processing which consists of filtering and normalization of the signal data. The data are labeled for the motion patterns with the camera video. Afterthen, characteristics features are extracted from the labeled triaxial data and a dimension reduction model is applied to reduce the features into a smaller number of category features. According to the characteristics of the helmet motions, the optimal model parameters and sensor selection are derived. Finally, a machine learning model is used to analyze the motion classification problem. The performance of the methodology is evaluated with real data collected in motorcycle riding experiments.

2. Sensors technologies with smart helmet

2.1. Sensors for head motion activity

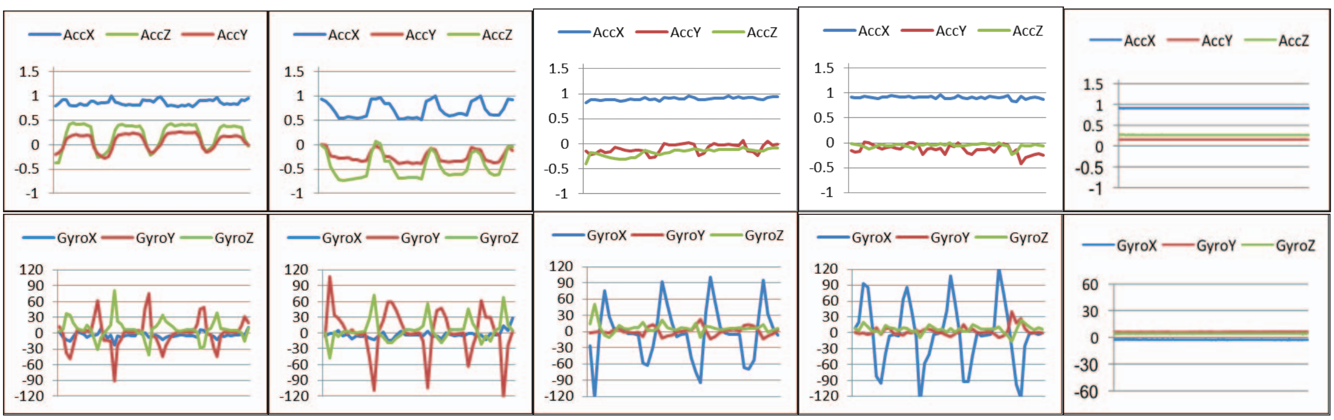
The equipment used in this study is a prototype smart helmet manufactured by JARVISH inc. (www.jarvish.com). It is a full-face helmet integrated with an intelligent system to connect with and control a smartphone wirelessly via Bluetooth or Wi-Fi. Voice commands can be used to control the functions including camera recording, telephone answering, volume adjustment, music playing, audio navigation etc.

The smart helmet is embedded with a FHD camera and an IMU sensors for motion detection (see Figure 1). The FHD camera is placed at the forehead position of the helmet and records the video of the front of the rider. The IMU sensor (LSM9DS1TR, consists of a 3D accelerometer with a range of ±16g, a 3D gyroscope with a range of ±2000°/s and a 3D magnetometer with a range of ±16 gauss) is placed at the inner side of the helmet positioned close to the back of the head.

FIGURE 1. Sensors and functions of the smart helmet

2.2. Data and IMU signal

The measurements consist of linear acceleration and angular velocity information collected from the accelerometer and gyroscope sensors of the smart helmet. Figure 2 shows the typical patterns in triaxial accelerometer and gyroscopic sensor signals for different head motion activities when the helmet wearer is riding a motorcycle. The four motions are: Looking up (LU), Looking down (LD), Turning left (TL) and Turning right (TR) and then returning to the initial orientation. Each motion is repeated four times in the signal illustration. The LU motion replicate the action that a rider reading traffic light mounted on a pole or gantry overhead whereas LD for a rider reading the mounted mobile phone mounted on the handlebar.



(a) (b) (c) (d) (e)

FIGURE 2. Triaxial accelerometer signals in g (top row) and triaxial gyroscope signals in degree per second (bottom row) when a user performs different head motions during riding a motorcycle. (a) Looking up. (b) Looking down. (c) Turning left. (d) Turing right. (e) Helmet idle as reference.

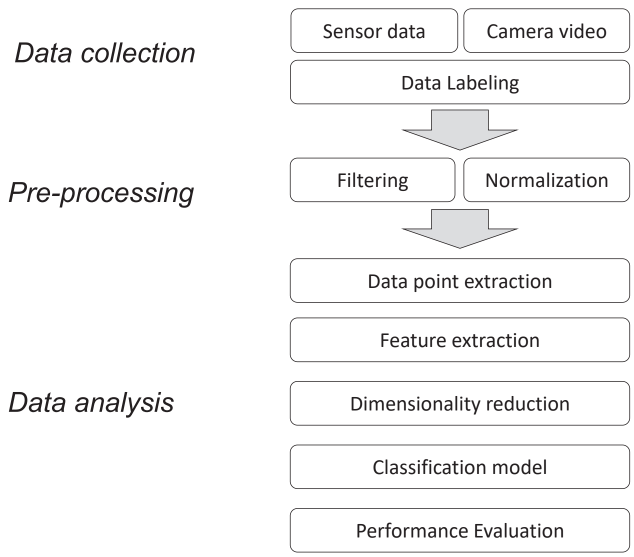


FIGURE 3. Framework of the methodology.

The rider makes a TL or TR when looking at the mirror or doing a head check. The sensor signals represent the measurements along the *x*, *y*, and *z* directions at the orientation of the sensors. The differentiation between the signal waveforms of different head motions facilitate accurate activity recognition. It can be seen that patterns corresponding to the head motions are distinct. For example, TL and TR produce a gyroscope signal in the *x* direction in opposite pattern but does not produce significant signals with accelerometer. As we can see, the gyroscopic signals provide more information than the accelerometer signals because head motions are performed with bending or twisting the neck. These observations provide insights in the design and selection of feature descriptors and sensor signals to effectively characterize these signal patterns.

3. Methodology

We propose a methodology for recognizing the head motions of motorcycle riders (see Figure 3). The model is then used for motion recognition of real riding data.

3.1. Data collection, visualization, and labeling

Recruited participants are asked to wear the smart helmet to ride a motorcycle. They perform various head motions and maneuvering actions under the instruction of a passenger with the rider. The signal measurements and videos are recorded with the sensors and camera of the smart helmet. The data are input for visualization and labeling with a data acquisition platform

3.2. Data preprocessing and feature extraction

The triaxial accelerometer and gyroscopic sensors are sensitive to vibrations and the signals record are subject to high-frequency noise. A low-pass filter is applied for each signal and then normalized to unit length.

3.3. Feature extraction

Each sensor returns a time-series signal and each motion of interest can be characterized from the data by feature extraction using a time window technique. Generally, a desired length of window is half of the complete wavelength of the signal to be recognized such that each window is overlapped by the following window to enhance the precision of recognition [12].

Therefore, the ideal length of time window may depend on the type and duration of the motion and a longer time window should be avoided because there could be a motion change during that duration.

Let the vector form of the triaxial accelerometer and gyroscope signals be $X = \{a_x, a_y, a_z, r_x, r_y, r_z\}$. The labeled data points with head motions of interest are illustrated in Figure 4. The accelerometer data shows a trend of clustering whereas the gyroscope data shows a trend of regression.

We considered seven time-domain statistical features namely, maximum, minimum, average, standard deviation, sum, variation and energy. Let the signal in the window be represented as $\{X_1, X_2, ..., X_{|W|}\}$ where X_i denotes the magnitude of the measurement at time t and $|W|$ is the length of the window. The statistical features are defined as follows:

(i) Maximum of the signal data values in the time window

$$\text{MAX} = \max\left(X_i, i = 1, ..., |W|\right), \quad (1)$$

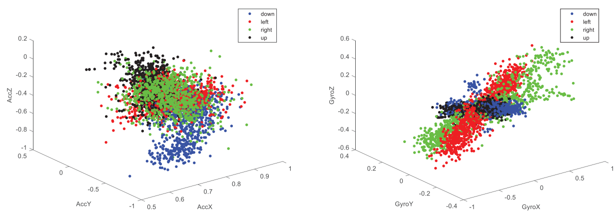
(ii) Minimum of the signal data values in the time window

$$\text{MIN} = \min\left(X_i, i = 1, ..., |W|\right), \quad (2)$$

(iii) Average of the signal data values in the time window

$$\text{AVG} = \frac{1}{|W|} \sum_{i=1}^{|W|} X_i \ , \quad (3)$$

(iv) Standard deviation of the signal data values in the time window



(a) (b)

FIGURE 4. Labeled data points. (a) Triaxial accelerometer. (b) Triaxial

$$\text{STD} = \sqrt{\frac{1}{|W|-1}\sum_{i=1}^{|W|}\left(X_i - AVG\right)^2} \quad (4)$$

(v) Sum of the signal data values in the time window

$$\text{SUM} = \sum_{1}^{|W|} X_i \quad (5)$$

(vi) Variation of the signal data values in the time window

$$\text{VAR} = \frac{1}{|W|-1}\sum_{i=1}^{|W|}\left(X_i - AVG\right)^2 \quad (6)$$

(vii) Energy: Average of squares of the signal data values in the time window

$$\text{ENERGY} = \frac{1}{|W|}\sum_{i=1}^{|W|}\left(X_i\right)^2 \quad (7)$$

3.4. Dimensionality reduction

Extracting seven characteristics features from the two triaxial sensors generates 42 features. This may include redundant or irrelevant information for the recognition and is a burden for further computing. Dimensionality reduction is applied to combine multiple features into a smaller number of new features which would be better suited for the dataset and recognition purpose.

Linear Discriminant Analysis (LDA) is employed for dimensionality reduction [13]. It maps high-dimensional data onto a calculated vector, separates data into various categories and tightens up data in each category. Dimensions with high feature value are then output as results. Two dispersion matrices, covariance matrices for between categories and within categories are adopted [12]. The predicted discrete vector values near the mixed averages is defined as

$$S_B = \sum_{\alpha=1}^{N} n_\alpha \left(m^\alpha - m\right)\left(m^\alpha - m\right)^T \quad (8)$$

and the predicted vector dispersion sample of each category is defined as

$$S_W = \sum_{\alpha=1}^{N} n_\alpha \sum_{i=1}^{n_\alpha}\left(x_i^\alpha - m^\alpha\right)\left(x_i^\alpha - m^\alpha\right)^T \quad (9)$$

where N denotes the number of categories; n_α is the number of samples in category α; x_i^α represents sample i of category α; m^α is the sample mean vector of category α, and m is the mean vector of all data. LDA produces mapping vector w to store the category integrity under low dimensionality such

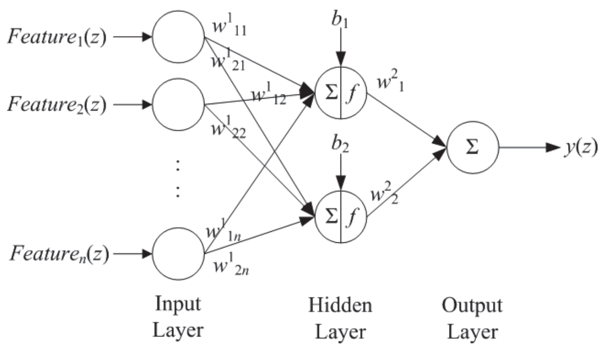


FIGURE 5. Structure of the neural network.

that the covariance between different categories is maximized and the covariance within a category is minimized. Therefore, w can be obtained by maximizing $J(w)$ below

$$J\left(w\right) = \frac{w^T s_B w}{w^T s_W w}. \quad (10)$$

Once w has been calculated, the data can be mapped onto coordinate systems and new coordinates can be identified to reduce dimensionality.

3.5. Motion classification and identification

A neural network model is applied for the classification and recognition of motion patterns. It is useful and efficient for applications dealing with complex analysis and signals from accelerometers and gyroscopic [14, 15]. The structure of the proposed neural network is presented in Figure 5 which includes an input layer, a hidden layer, and an output layer. The input layer receives the features selected by the LDA, which are then related to the hidden layer. Thus, the number of nodes in this layer must equal the number of selected features. The hidden layer merges the features and then uses a set of activation functions to formulate the relationship between the features and the motions. Details of the procedure are described in [14]. After training the neural network, the feature set is input to enable the identification of rider's head motions.

4. Results

The procedure is coded in MATLAB and the neural network model is trained and validated with a dataset consisting 407 labeled data points. The data are randomly divided into training data, validating data and testing data at the ratios 70%, 15% and 15% respectively. The training data is used for the estimation and calibration of the neural network and the validation data is repeatedly used to estimate the non-training performance error of the model to check the model convergence. The number of hidden neurons for the neural network model is set to 10.

4.1. Sensor selection and LDA

The recognition performance depends on the discriminative power of the information extracted from the sensors. With LDA, the maximum number of features after dimensionality reduction is N-1 where N is the number of classes for classification. Thus, the full feature sets can be reduced to three features or fewer. Accelerometer and gyroscope sensors are good at different kind of motions. Some previous studies suggested that only accelerometer sensor data is good for some applications [5, 12, 16]. On the other hand, gyroscope sensor data is effective in identifying pattern involving turning [17]. When LDA reduces the features into a limited feature space, we have to select carefully which combinations of sensors would be good for the recognition of head motions which involves head rotation.

A sensor data selection approach is applied by training and validating the neural network model using different data subsets: (i) triaxial accelerometer data only, (ii) triaxial gyroscope data only and (iii) both triaxial dataset when only three or fewer discriminants are to be extracted. The results are given in Table 1. The correct classification rates are improved when there are more discriminants. The best result is the gyroscope data using three discriminants with 97.5%.

4.2. Performance evaluation

To identify the classification accuracy of the motion patterns by neural network model, the global confusion matrix using gyroscope data reducing to three discriminates is given in Table 2. The result reveals that the four motions, LU, LD, TL and TR, are well recognized with 99.1%, 97.9%, 97.2%, and 95.9%, respectively. In overall, the correct classification rate for training, validation, testing and all are 98.2%, 95.1%, 96.7% and 97.5% respectively. The head motions can be identified successfully with a high level of accuracy.

There are some confusions between the motion pairs [LU, LD] and [TL, TR]. Those motion pairs are opposite motions with similarity in the dynamic of the rider but opposite in directions. For example, TL denotes the action that the rider turning the head to the left and then returning to the face forward orientation and it can be decomposed into a yawing counterclockwise signal followed by a yawing clockwise signal along the axis of the body, as in Fig. 2(c).

TABLE 1. Rate of correct classification

Triaxial sensor type	**Number of discriminants for LDA**		
	1	2	3
Triaxial accelerometer	39.1	42.5	73.7
Triaxial gyroscope	74.9	92.4	**97.5**
Both sensors	45.9	52.6	75.4

In contrast, TR motion has a yawing clockwise signal followed by a counterclockwise signal as in Fig. 2(d). Both motions include a counterclockwise signal and a clockwise signal with similar amplitude but different signs and misclassification arises if the sequence of the two signals cannot be accurately extracted with the features and time window technique. The same explanation applies to the LU and LD motion pair.

TABLE 2. Confusion matrix for the motion classification

		Target Class (%)			
		LU	**LD**	**TL**	**TR**
Output class	**LU**	99.1	2.1	0	0
	LD	0	97.9	0	0
	TL	0	0	97.2	4.1
	TR	0.9	0	2.8	95.9

The classification problem considered in this study with discrete motions is challenging as compared to the activity recognition problems with continuous motions (e.g. walking up stairs) because the time taken to complete a motion may vary between motions and user behaviors. This is important for head motion classification if it is necessary to distinguish motion types such as shoulder check and mirror check which have similar head rotations but with meticulous differences. In a future study, a recognition model will be proposed to consider the duration length and amplitude of motions.

5. Conclusions

A smart helmet is a lower-cost option in providing rich information for the riders' head motions. A methodology is proposed to extract the most discriminant features from the sensors data for the calibration of the classification model. The results show that the proposed model can effectively recognize the head motions. The sensor selection analysis reveals that gyroscope sensor data are more significant than accelerometer data if used alone because head turning movements generate a perceptible signal to the gyroscope.

Acknowledgements

This work was supported by the Ministry of Science and Technology of Taiwan (Project No. MOST 105-2634-F-009-001). The authors would like to thank JARVISH Inc. (http://www.jarvish.com) for providing the equipment and their technical support for the data collection.

References

[1] S. C. Mukhopadhyay, "Wearable Sensors for Human Activity Monitoring: A Review," *IEEE Sensors Journal,* vol. 15, no. 3, pp. 1321-1330, 2015.

[2] A. Nag, S. C. Mukhopadhyay, and J. Kosel, "Wearable flexible sensors: A review," *IEEE Sensors Journal,* vol. 17, no. 13, pp. 3949-3960, 2017.

[3] A. Jain and V. Kanhangad, "Human Activity Classification in Smartphones using Accelerometer and Gyroscope Sensors," *IEEE Sensors Journal,* 2017.

[4] M. Cornacchia, K. Ozcan, Y. Zheng, and S. Velipasalar, "A survey on activity detection and classification using wearable sensors," *IEEE Sensors Journal,* vol. 17, no. 2, pp. 386-403, 2017.

[5] P. Li, R. Meziane, M. J. D. Otis, H. Ezzaidi, and P. Cardou, "A Smart Safety Helmet using IMU and EEG sensors for worker fatigue detection," in *2014 IEEE International Symposium on Robotic and Sensors Environments (ROSE) Proceedings*, 2014, pp. 55-60.

[6] W. V. Rosenberg, T. Chanwimalueang, V. Goverdovsky, D. Looney, D. Sharp, and D. P. Mandic, "Smart Helmet: Wearable Multichannel ECG and EEG," *IEEE Journal of Translational Engineering in Health and Medicine,* vol. 4, pp. 1-11, 2016.

[7] M. K. A. M. Rasli, N. K. Madzhi, and J. Johari, "Smart helmet with sensors for accident prevention," in *2013 International Conference on Electrical, Electronics and System Engineering (ICEESE)*, 2013, pp. 21-26.

[8] E. I. Vlahogianni and E. N. Barmpounakis, "Driving analytics using smartphones: Algorithms, comparisons and challenges," *Transportation Research Part C: Emerging Technologies,* vol. 79, pp. 196-206, 2017/06/01/ 2017.

[9] H. Eren, S. Makinist, E. Akin, and A. Yilmaz, "Estimating driving behavior by a smartphone," in *Intelligent Vehicles Symposium (IV), 2012 IEEE*, 2012, pp. 234-239: IEEE.

[10] D. A. Johnson and M. M. Trivedi, "Driving style recognition using a smartphone as a sensor platform," in *Intelligent Transportation Systems (ITSC), 2011 14th International IEEE Conference on*, 2011, pp. 1609-1615: IEEE.

[11] J. Windau and L. Itti, "Walking compass with head-mounted IMU sensor," in *2016 IEEE International Conference on Robotics and Automation (ICRA)*, 2016, pp. 5542-5547.

[12] J.-Y. Yang, Y.-P. Chen, G.-Y. Lee, S.-N. Liou, and J.-S. Wang, "Activity recognition using one triaxial accelerometer: A neuro-fuzzy classifier with feature reduction," *Entertainment Computing–ICEC 2007,* pp. 395-400, 2007.

[13] Y. Jieping, L. Qi, X. Hui, H. Park, R. Janardan, and V. Kumar, "IDR/QR: an incremental dimension reduction algorithm via QR decomposition," *IEEE Transactions on Knowledge and Data Engineering,* vol. 17, no. 9, pp. 1208-1222, 2005.

[14] J.-S. Wang and Y.-C. Chen, "A Hammerstein-Wiener recurrent neural network with universal approximation capability," in *2008 IEEE International Conference on Systems, Man and Cybernetics*, 2008, pp. 1832-1837.

[15] K. Choi, K.-A. Toh, and H. Byun, "Realtime training on mobile devices for face recognition applications," *Pattern Recognition,* vol. 44, no. 2, pp. 386-400, 2011/02/01/ 2011.

[16] J. S. Wang and F. C. Chuang, "An Accelerometer-Based Digital Pen With a Trajectory Recognition Algorithm for Handwritten Digit and Gesture Recognition," *IEEE Transactions on Industrial Electronics,* vol. 59, no. 7, pp. 2998-3007, 2012.

[17] F. Attal, A. Boubezoul, L. Oukhellou, and S. Espié, "Powered Two-Wheeler Riding Pattern Recognition Using a Machine-Learning Framework," *IEEE Transactions on Intelligent Transportation Systems,* vol. 16, no. 1, pp. 475-487, 2015.