BED POSTURE CLASSIFICATION BY NEURAL NETWORK AND BAYESIAN NETWORK USING NONINVASIVE SENSORS

BY

WARANRACH VIRIVAVIT

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING (INFORNATIOMATION AND COMMUNICATION TECHNOLOGY FOR EMBEDDED SYSTEMS)
SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY
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A Thesis Presented

By

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Submitted to

Sirindhorn International Institute of Technology

Thammasat University

In partial fulfillment of the requirements for the degree of

MASTER OF ENGINEERING (INFORMATION AND COMMUNICATION TECHNOLOGY FOR EMBEDDED SYSTEMS)

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JULY 2017

Acknowledgements

This research is financially supported by Thailand Advanced Institute of Science and Technology (TAIST), National Science and Technology Development Agency (NSTDA), Tokyo Institute of Technology, Sirindhorn International Institute of technology, Thammasat University under the TAIST Tokyo Tech Program. The sensor panel and IP camera are supported by AIVS Co., Ltd. The videos and patients data are collected under the permission of the patients and acknowledgement of Banphaeo Hospital.

Abstract

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The elderly population of the world continues to increasing rate. In Thailand, the proportion of elderly people is also growing up to 14.9% in 2014. The national statistical office of Thailand reports that percentage of living alone elderly is rising from 3.6 in 2002 to 10.4 in 2014. Hence, it needs more geriatric care. Elderly have a high risk of falling down when they attempt to get out of bed in order to go to a bathroom. 7.8% of them are hospitalized. This accident has a high risk of serious injury such the bone fracture. To prevent an accident around a bed, one of the effective approaches is the ability to detect gestures on a bed, then the system provides enough time for assist his/her movement. Such a monitoring system will help to reduce the burden of nurses and caregivers. Moreover, a hospitalized elder is usually restricted on a bed with cable or tubes. Then they have a high risk of losing the skill of activity in daily life because of less mobility. Corresponding to the concern of loss functional ability in elderly, a non-invasive sensor is appropriate to be used for monitoring the elderly behavior. In previous works, some studies use commercial pressure mat system to classify postures on a bed for a privacy reason, unlike the system with a camera. However, those of studies require a large number of sensing array which is not practical and costly. Therefore, our approach uses a sensor panel, which consists of only four sensors i.e. two piezoelectric sensors and two pressure sensors. The sensor panel is applied under the mattress in thoraces area. Our approach collects data from elderly patients in hospital with five different postures i.e., out of bed, sitting, lying down, lying left, and lying right. Neural Network approach is used to classify 5 postures and evaluate feature input, i.e. 4 inputs, 120 inputs, 4 inputs with normalized signal, 120 inputs with normalized signal. The 4 inputs are transaction signal from 4 sensors i.e., right piezoelectric signal, left piezoelectric signal, right pressure signal, right pressure signal. The 120 inputs are accumulated signal data in one second time slots. To eliminate the effect of weight and bias between different types of sensors, the unity based normalization (or feature scaling) method is used to normalize sensor data into the range of 0 to 1. The results of 120 inputs with normalized signal reach up to 100% of accuracy. In the full dataset, the accuracy decreases from 100% to 94.10% because of noise and unclean dataset. To eliminate to unexpected result of the output posture from the Neural Network model, the Bayesian Network is adopted to estimate the likelihood of the consecutive postures. We then combine the results from both Neural Network probability and Bayesian probability by the weight arithmetic mean. The experimental results yield the maximum accuracy up to 94.65% when the coefficient of Bayesian probability and a Neural Network are set to 0.7 and 0.3 respectively. Our approach uses only 4 sensors without losing much in performance when comparing to the previous approaches.

Keywords: Bed Classification, Neural Network, Bayesian Network, Elderly care

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Chapter 1
Introduction

1.1 Objective

The percentage of elderly people in Thailand is increasing from 12.2% in 2011 to 14.9% in 2014 [1], and then Thailand will become an aged society in 2020 [2] as shown in Figure 1.1. According to the figure, there will be more needs of geriatric care in the coming years. The national statistical office of Thailand reports that the percentage of single elderly is growing up to 10.4% in 2014 because of changing of social structure. This requires more resources and cost.

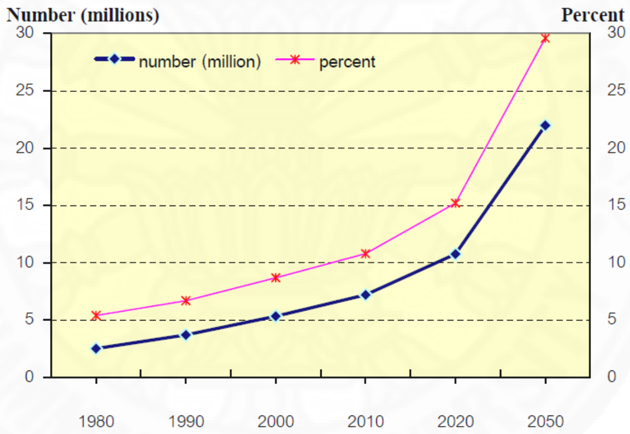


Figure 1.1 Elderly population in Thailand

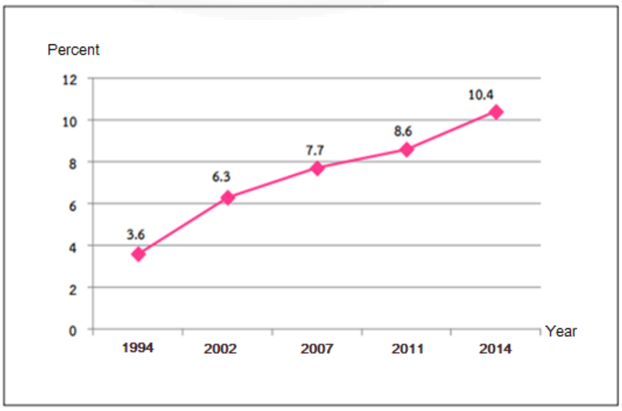


Figure 1.2 Percentage of single elderly

When an elderly person attempts to get out of bed in order to go to the bathroom, he/she has high risk of falling down. This accident has the high probability of serious injury, such as a bone fracture. From the 2014 survey of the older persons in Thailand, 39% of elderly fall down by stumbling over obstacles, 46.3% of them are treated and 7.8% of them are hospitalized as in-patient [1]. Hospitalized elderlies have a high risk of loss activity function in daily life. They are normally restricted to a bed with cable or tube. Because of less mobility, their muscle become weaker. Therefore, they have a risk of falling down again.

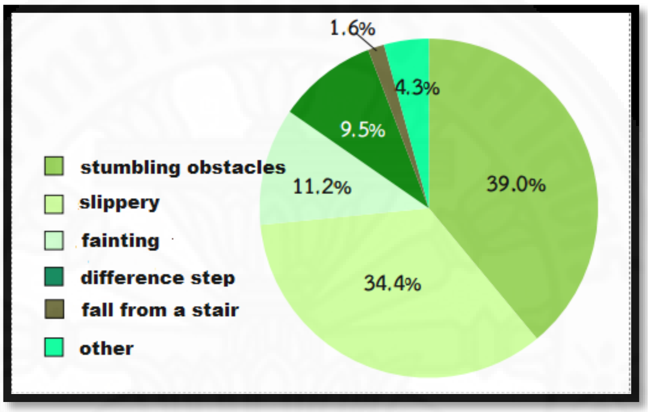


Figure 1.3 Cause factor of falling down

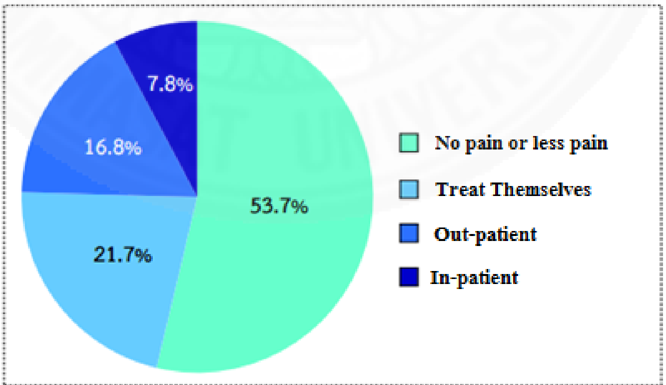


Figure 1.4 Percentage of treatment from falling down

The patient safety is vital for nurse intervention [3]. Hence, preventing a falling down, one of effective approaches is ability in human on-the-bed gesture classification. Then, the system provides enough time to assist his/her movement which can help to decrease burden of nurses and caregivers.

The commercial pressure mat system is used to classify human on-the-bed gesture for a privacy reason, unlike monitoring with a camera [8-17]. However, the pressure mat system is required a large number of sensors. Some studies used sensors with cable e.g., electrodes, finger bend. However, those of sensors are not appropriate to monitor elderly behavior, responding to the concern of loss activities skill in daily life. Therefore, our approach proposes use the minimum number of noninvasive sensors for detecting postures on a bed. The on-a-bed postures is classified by is using Neural Network (NN). Some posture signals have a similar pattern thus Bayesian Network is used to eliminate unexpected results from the Neural Network outputs

1.2 Scope

In my experiment, the elderly behaviors on a bed are collected in a real environment like a hospital. Three elderly patients whose age more than 60 participated in the experiment. Total data are taken for 459 hours. Also, to assert that various environments and patients' conditions do not have any effect toward this experiment, the data is collected from two rooms which is used different sets of sensors. The data of two elderly patients are collected from room 1 and another one from room 2. The data is composed of streaming video and sensor signals from a sensor panel. Because of privacy reason, nakedness is not permitted to collect. The sensor panel is placed beneath a mattress in the thoracic area. It is consisted of vibration sensors and pressure sensors for detecting posture. The on-a-bed postures are identified into 5 classes i.e. out of bed (O), sitting (S), lying down (L), lying left (LL), and lying right (LR). Definition of each posture is as follows:

Out of bed (O):	Nobody on a bed
Sitting (S):	Sitting on a bed
Lying down:	Supine or prone sleeping position
Lying left (LL):	Lying on left hand side of a bed
Lying right (LR):	Lying on right hand side of a bed

Lying left (LL) and Lying right (LR) postures are defined as lying on either left or right side of a bed regardless of any lateral position. Neither ambiguous postures nor changing movement do not consider in this experiment.

1.3 Outline of the proceeding chapters

Chapter 2 reviews previous studies. The various methods of posture classification, number of identifying postures, and number of sensing array are shown. Chapter 3 shows the experimental method and describes the posture classification method. The results are illustrated and discussed in Chapter4. Finally, Chapter 5 shows conclusion and discussion of a future work.

Chapter 2
Literature Review

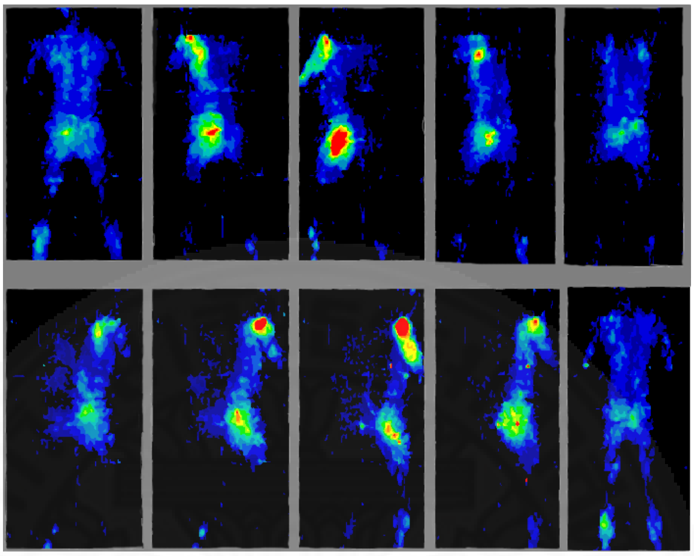


Figure 2.1 Pressure mat system

(Ref: https://www.tekscan.com/products-solutions/systems/body-pressure-measurement-system-bpms-research)

A commercial pressure mat system is widely used to classify on-a-bed postures [8-17]. Pressure sensors are distributed over a bed surface in an array as mat. Two major types of available pressure sensors are resistive and capacitive. Currently, a pressure sensor array is offered in a market e.g. Tekscan, Xsensor, Sensor Product Inc. as shown in Figure 2.1

Figure 2.2 Sleep posture

Most of studies use pressure sensor arrays for bed posture classification. Those of studies classify different sleeping postures which are identified in 3 major types i.e. side-sleeping, back-sleeping, and stomach-sleeping. Actually, the on-a-bed posture patterns can be categorized into various position e.g. supine, prone, foetus, log, yearner as shown in Figure 2.2. The aforementioned studies applied various different techniques e.g. binary pattern matching, Gaussian mixture model (GMM), a pictorial structure method [8-17]. Also, a machine learning approach has been applied for detecting posture on a bed e.g. deep neural network (DNN), support vector machine (SVM), principal component analysis (PCA) [10, 12-16]. M. B. Pouyan et al. present continuous monitoring system. The binary pattern matching is used to classify eight postures on a bed [8]. Sarah Ostadabbas et al. detect sleeping postures and identify different body limbs by using Gaussian mixture model (GMM) method [9]. Rasoul Yousefi et al. classify 5 sleep postures by using support vector machine (SVM) and principal component analysis (PCA) [10]. J. Liu Jason et al. use a pictorial structure method to detect the lying postures [11]. M. Heydarzadeh et al. apply deep neural networks (DNN) to automatically classify on-bed postures using features extracted from the histogram of gradient (HoG) technique [12] W. Cruz-Santos et al. demonstrate posture recognition using a low-resolution pressure sensor array. They use support vector-machine (SVM) to classify 4 on-a-bed postures [13] R. Yousefi et al. detect patient's bed postures by using principal component analysis (PCA) [14]. W. Huang et al. propose a multimodal approach to classify 6 sleeping postures. The posture patterns are characterized by using pressure sensor map and video image [16]. However, the aforementioned studies require a large number of sensors which are costly and not practical. Hence, some studies present approaches to reduce the number of sensing array. For instance, C. C. Hsia use Kurtosis and skewness estimation, principal component analysis (PCA) and support vector machines (SVMs) for bed posture classification. They reduce number of sensors from 56 to 16 sensors as shown in Figure 2.3 [15, 17]. This approach has the minimum number of sensors in aforementioned studies.

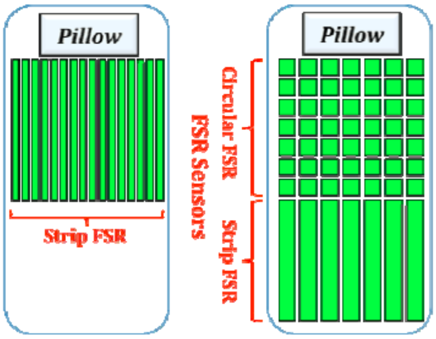


Figure 2.3 Sensing Bed Configuration with 16-sensor and 56-sensor Pads in C. C. Hsia et al. [15]

There are some studies use 4 spot sensors to detect postures on a bed. Those of sensors set under the legs of a bed. For example, T. Shino et al. use ceramic piezo devices to determine body-movement biosignals. [5]. S. Nukaya et al. propose the relationship between sensor signals and movement on a bed. The integrated signal of those sensors can be identify movement on a bed [6]. A. Gaddam et al. demonstrate the sensors signal response from applying weight in various positions. This system is not only determine whether a patient is in the bed or not but it can precisely indicate the patient's position on the bed [7].

By the way, some studies use other types of sensor for bed posture classification e.g. electrode, ultrasonic sensor, air pressure, finger bend, accelerometer [18-21]. H. J. Lee et al. applied linear discriminant analysis, support vector machines (SVM) with linear and radial basis function (RBF) using 12 electrodes of ECG [18]. M. Cholewa et al. analyze 22 natural gestures with three sets of sensors i.e. five finger bend, three accelerometers and two pitch/roll. The Hidden Markov Model and Bayesian Network are used [21]. Both of studies are not appropriate to monitor elderly behavior because the elderly will gradually lose their skill activity functions by the restriction with the cables or tubes [3].

Other studies apply Fuzzy inference technique to detect behavior on a bed by using only two sensors i.e. ultrasonic sensor and air pressure. However, the proposed studies can just only detect the mere presence of a patient on a bed [19, 20].

Chapter 3
Experiment

3.1 Collecting data

3.1 1 Sensing equipment

Figure 3.1 Sensor panel

The sensor panel is a ready-made set of sensors from AIVS Co., Ltd. as shown in Figure 3.1. Two types of sensors i.e. two piezoelectric sensors and two pressure sensors are embedded on each side of the panel. The magnitude of each sensor is 256. The piezoelectric signals have a range of value between 127 to 128. The range of value of pressure signal is between 0 to 256. The sampling rate of each sensor is 30 Hz. The control device outputs a series of packages of data in each time. Figure 3.2 shows detail of data structure. The data package contains 45 bytes. It is divided into 3 parts in the sequence of header, four sensors, and ender. There are 8 bytes of header and 3 bytes of ender. The sensing data is then formed a package of 34 bytes between header and ender, where the first two bytes contain the sensor's ID, and other 32 bytes are the signal data i.e. left piezoelectric signal, left pressure signal, right piezoelectric signal, and right pressure signal, respectively.

Header	Sensors address	Piezo 0	Weight 0	Piezo 1	Weight 1	Ender
8 byte	2 byte	8 byte	8 byte	8 byte	8 byte	3 byte

Figure 3.2 Data structure

Figure 3.3 Position of sensor panel on a bed

The sensor signals and video data are synchronized with time stamp. The postures are labeled into five classes i.e. out of bed (O), sitting (S), lying down (L), lying left (LL), and lying right (LR) by observing the capture video. The panel sensor is set under a mattress in the thoracic area as shown in Figure 3.3. By placing the panel in such position, the signals of both side of sensors can distinguish the postures on a bed as shown in Figure 3.4. For instance, in out of bed posture, the activation of piezoelectric sensors is low in contrast to on bed postures (i.e. sitting, lying down, lying left, and lying right) of which the high signals from piezoelectric sensors can be detected. In sitting posture, the pressure signals from both sides of sensors are low but the activation of piezoelectric sensors are still detected in contrast to out of bed posture which is the very low signals from all sensors. In lying down posture, the body pressure on both sides of the sensors whereas lying left or right, only one side of the sensor is activation.

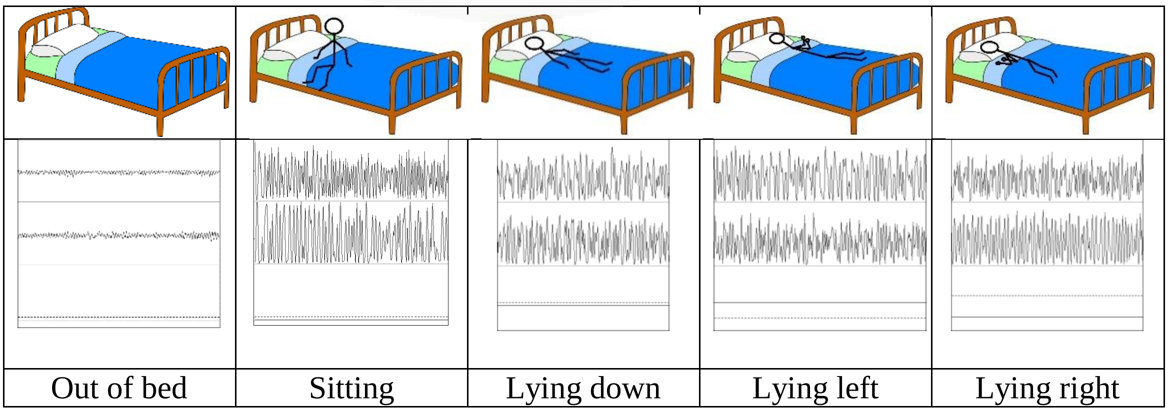


Figure 3.4 Relationship between sensor signals and postures. [Above] The first bold line is signal of piezoelectric sensor on left side, the second bold line is signal of piezoelectric sensor on right side. [Below] Bold line is signal of pressure on left side, and dash line is signal of

pressure on right side

3.1 2 Dataset

3.1.2.1 Primary Experiment

The selected datasets are prepared by eliminating the possible noise of the signal as a clean dataset. The structure of dataset is shown in Figure 3.5. Each set of data is included of 30 signal units × 4 sensors = 120 samples, to make a one second time slot. Normally, one posture in one time interval can last in more than one second. Therefore, there can be as many time slots as possible in one time interval of a posture.

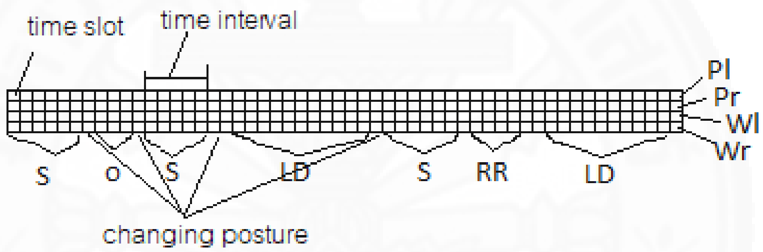


Figure 3.5 Structure of dataset

(1) Dataset for evaluating feature input

To evaluate features of input, the inputs are categorized into four types i.e. 4 inputs, 120 inputs, 4 inputs with normalized signal, and 120 inputs with normalized signal. Those of datasets are defined into five types, i.e. subject A, subject B, subject C, combination of subject A and B in the same room, and combination of data from two rooms. The selected datasets include 2,000 sets (5 postures x 400 sets) from each subject in room 1 and 1,335 (5 postures x 267 sets) sets from subject in room 2. In case of two rooms, 5,335 sets (5 postures x 1067 sets) of data is selected. The dataset of each subject is selected from different 4 time intervals in each posture. The dataset is divided into 70% for training and 30% for testing as shown in Table 3.1.

Table 3.1 Number of time interval

Posture	Clean dataset				Total	
	Train		Test			
	# of sample	# of time interval	# of sample	# of time interval	# of sample	# of time interval
Out of bed	747	12	320	12	44172	42
Sitting	747	12	320	12	32012	160
Lying down	747	12	320	12	90486	111
Lying left	747	12	320	12	4820	26
Lying right	747	12	320	12	222643	173

(2) Dataset for evaluating hidden node

The 120 inputs with normalized signal data are used for evaluating hidden node. The combination of data from two rooms is selected to be dataset. The dataset is split into 70% for training and 30% for testing as shown in Table 3.1. There are 12 different time intervals.

(3) Dataset for validating dataset

The 120 inputs with normalized signal data of each data are input of Neural Network model. To validate dataset, the model are divided into three model i.e. training, validation, and testing. The dataset are categorized into three set i.e. subject A, combination of subject A and B in the same room, and combination of data from two rooms. For example, dataset of subject A is include 1600 sets (5 postures x 320 sets) for training and 800 sets (5 postures x 160 sets) for validation. In testing dataset of subject A is 2000 sets (5 postures x 400 sets) from subject B. In case combination of subject A and B in the same room, 3200 sets(5 postures x 640 sets) for training and 1600 sets(5 postures x 320 sets) for validation are used. The dataset of subject C (Room 2) is used for testing. The combination of data from two rooms is include 4268 sets (5 postures x 400 sets) for training and 1067 sets (5 postures x 400 sets) for validation.

3.1.2.2 Evaluate test

(1) Dataset for Bayesian Network approach and combination of Neural Network and Bayesian Network approach

The dataset is extended on the total data of subject A which is about 390,000 sets. The dataset size of the 5 postures i.e. out of bed, sitting, lying down, lying left, and lying right is about 44,000, 32,000, 90,000, 4,800, and 220,000, respectively. The number of time interval of each posture is 42, 160, 111, 26, and 173, respectively. For classifying postures in the Neural Network model, the dataset is divided into 70% for training and 30% for testing.

3.2 Posture detection

3.2.1 Evaluation of feature input

3.2.1.1 Raw data

(1) 4 inputs

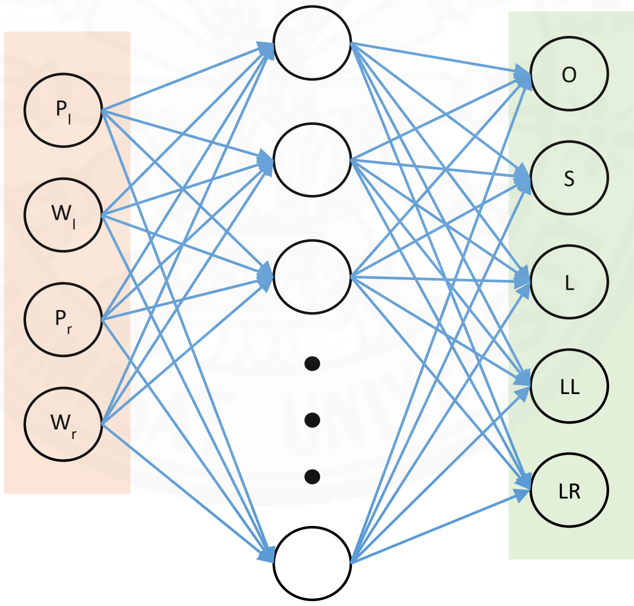


Figure 3.6 Neural Network diagram of four input signals, where O is out of bed, S is sitting, L is lying down, LL is lying left, LR is lying right

To classify postures on a bed, the 4 inputs from the control device i.e. left piezoelectric signal (P_l), right piezoelectric signal (P_r), left pressure signal (W_l) and right pressure signal (W_r) are used. These 4 inputs as described in (1) are passed through a Neural Network as shown in Figure 3.6.

$$X = \{x_1, x_2, x_3, x_4\} = \{P_l, W_l, P_r, W_r\} \tag{1}$$

(2) 120 inputs

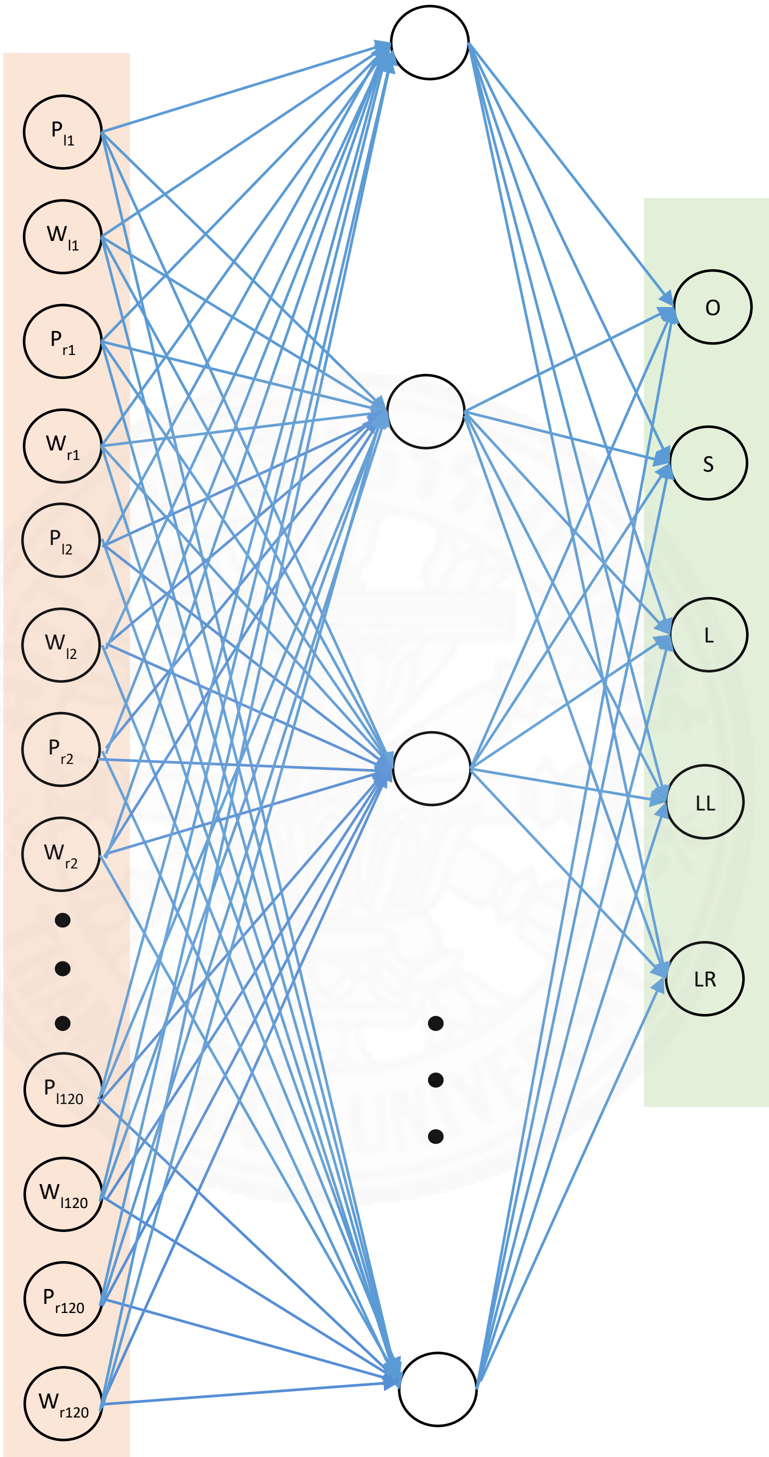


Figure 3.7 Neural Network diagram of 120 input signals, where O is out of bed, S is sitting, L is lying down, LL is lying left, LR is lying right

The 120 inputs is accumulated data in one second. From the properties of control device, the sampling rate of each sensor is 30Hz. Thus there needs 30 x 4 = 120 data signals as described in (2).

$$X = \{x_1, x_2, x_3, \dots, x_{120}\} = \{P_{l1}, W_{l1}, P_{r1}, W_{r1}, P_{l2}, W_{l2}, P_{r2}, W_{r2}, \dots, P_{l30}, W_{l30}, P_{r30}, W_{r30}\} \quad (2)$$

Then the 120 inputs are passed through a Neural Network as shown in Figure 3.7

3.2.1.1 Normalize data

The Normalized data can eliminate the bias of weight from different bodies and different types of sensor. All sensor data are normalized by using unity-based normalization as (3) [22].

$$X_i = \frac{x_i - min}{max - min} \quad (3)$$

Where x_i is the sensor data in i^th sequences, X_i is the normalized data, *min* is the minimum value, and *max* is the maximum value of the data collection

3.2.2 Evaluation of hidden node

The dataset is applied on varies number of hidden nodes until the accuracy is constant.

3.2.2 Bayesian Network approach

A Bayesian Network [23] is adopted to estimate next possible postures. This can decrease unexpected results and noise from an uncontrolled environment. The probability of the consecutive postures can be estimated by previous 2 postures and current signals as describe in (4) and (5).

$$P(S,P) = P(S)P(P|S) = P(P)P(S|P) \tag{4}$$

$$P(S,P) = P(P_i|P_{i-1}, P_{i-2})P(S|P_i) \tag{5}$$

Where $P(x)$ is a probability of x, $P(a|b)$ is a probability of a given b, $P(a,b)$ is a probability of a and b, P_i, P_{i-1} and P_{i-2} are posture in i^{th} sequences. S is the current set of signals consisting of four sensor signals (P_l, W_l, P_r, W_r). The continuous value of the signal data is converted to nominal value by dividing the signals into three levels i.e. low, middle, and high. The ranges of piezoelectric signal, 0-25, 26-50, and 51-100 are defined as low, middle, and high, respectively. The ranges of pressure signal, 0-35, 36-70, and 70-100 is defined as low, middle, and high, respectively.

3.2. 4 Combination of Neural Network and Bayesian Network

We combine the results from both Neural Network and Bayesian network approach by the weighted arithmetic mean shown in (6).

$$\alpha N + \beta B = C \tag{6}$$

Where N is Neural Network probability, B is Bayesian probability, C is classes and α, β are the coefficients which the sum of α and β is 1.

Chapter 4
Experiment Result

4.1 Results of Feature Input Evaluation

The result of feature evaluation is tabulated in Table 4.1. The overall performance on the 120 inputs with normalized signal can reach 100% of accuracy. In total, the model based on the normalized signal can work better raw signal. Like the model based on accumulated signal as 120 inputs, it give better results when compared to 4 inputs feature. The trained model can also work well in all situations.

Table 4.1 Input Feature

Dataset	**Input**			
	Raw signal data		**Normalized signal data**	
	4 input	**120 input**	**4 input**	**120 input**
A (Room 1)	99.3	99.8	99.6	99.9
B (Room 1)	99.5	100	100	100
C (Room 2)	99.9	99.9	100	99.9
A+B (Room 1)	97.6	98.2	98.2	98.8
Room 1 + Room 2	97.2	98.1	98.5	100

Considering confuse matrix as shown in Figure 4.1, the results of 120 input features achieved accuracy than the 4 input features. In the results of 4 input features, there are ambiguous in two classes i.e. out of bed and sitting. The accuracy of out of bed posture is 99.2% and sitting posture is 93.2%. Figure 4.2 shows the signal pattern of out of bed and sitting postures. Both of signals are quite similar. In sitting posture, pressure sensors are low activation, similar to out of bed posture, but no piezoelectric signals. Therefore, the signals of both postures are look the same at some point. The accumulated signal as 120 inputs can achieve accuracy of 100% for 5 postures classification whereas 4 input type reach only 99.5%. Hence, the accumulated signal can solve the confusion between out of bed and sitting posture. This is because Neural Network can capture more context feature to identify the out of bed posture from sitting posture.

Target class

a) 4 inputs	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	99.2	0.8	0	0	0
Sitting	6.8	93.2	0	0	0
Lying down	0	0	100	0	0
Lying left	0	0	0	100	0
Lying right	0	0	0	0	100

output

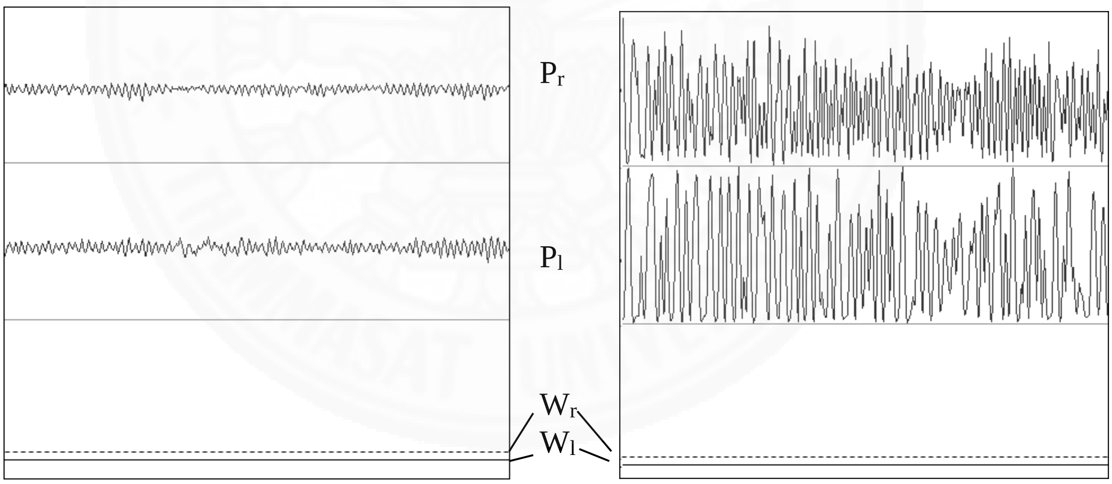
Target class

b) 120 inputs	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	100	0	0	0	0
Sitting	0	100	0	0	0
Lying down	0	0	100	0	0
Lying left	0	0	0	100	0
Lying right	0	0	0	0	100

output

a) 4 inputs b) 120 inputs

Figure 4.1 Confuse matrix of posture classification of subject B



a) Signals of out of bed posture b) Signals of sitting posture

Figure 4.2 Similarity of the signal patterns between out of bed posture and sitting posture

Figure 4.3 shows confusion matrix of 5-postures classification using combination of data from two rooms. The accuracy of 120 inputs type is noticeably higher than 4 inputs type in out of bed and sitting posture. Also, the accuracy of normalized signal is higher than raw signal for 5 postures classification. Due to different rooms, the environment such weight of mattress affect to value of signals. The 120 inputs with normalized signal can achieve 100% of accuracy. Therefore, the normalized signal data can eliminate bias of different type of sensors and weight effect.

a)

Output \ Target class	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	97.1	2.9			
Sitting	8.1	90.6		1.3	
Lying down			99.5		0.5
Lying left	0.7	0.2		99.1	
Lying right			0.1		99.9

b)

Output \ Target class	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	99.1	0.9			
Sitting	2.3	95.6		2.1	
Lying down			99.4		0.6
Lying left	1	0.7		98.3	
Lying right					100

c)

Output \ Target class	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	99.2	0.8			
Sitting	2.4	94.8		2.8	
Lying down			97.6		2.4
Lying left	0.9			99.1	
Lying right			0.1		99.9

d)

Output \ Target class	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	100	0	0	0	0
Sitting	0	100	0	0	0
Lying down	0	0	100	0	0
Lying left	0	0	0	100	0
Lying right	0	0	0	0	100

Figure 4.3 Confuse matrix of posture classification of combination of data from two rooms. a) 4 inputs b) 4 inputs with normalized signal c) 120 inputs d) 120 inputs with normalized signal

4.2 Results of Hidden Node Evaluation

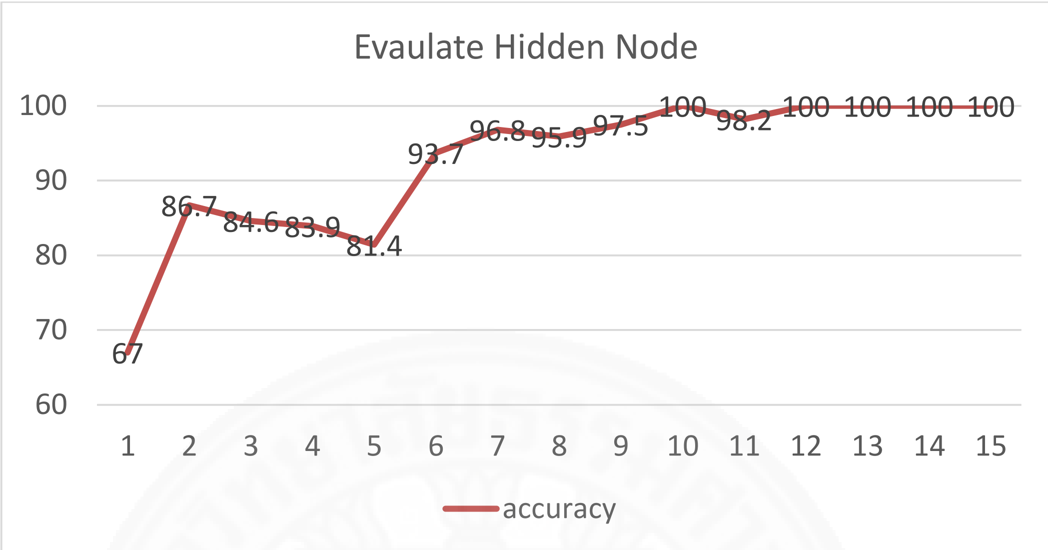


Figure 4.4 Hidden node evaluation

Figure 4.4 shows the graph of hidden node evaluation. Y axis is percents of accuracy and X axis is number of hidden node. The accuracy becomes constant as 100% in 12 nodes. Therefore, 12 hidden nodes is appropriate to use in the neural network model for bed posture classification.

4.3 Results of dataset validation

Table 4.2 Accuracy of validation test set

Dataset	Training	Validation	Testing
Subject A	100	93.7	88.8
Room 1	99.6	96.1	41.4
2 Rooms	90.5	89.6	

Table 4.2 shows accuracy of each dataset. In validation set, the accuracy decrease from training set but it is not losing much in accuracy. However, in case of cross validation in data from room 1. In testing set, dataset of room 2, the accuracy is noticeably lower than training and validation set. Therefore the suitable dataset for neural network model is the combination of data from two rooms.

4.4 Estimation of Consecutive Posture by Bayesian Network

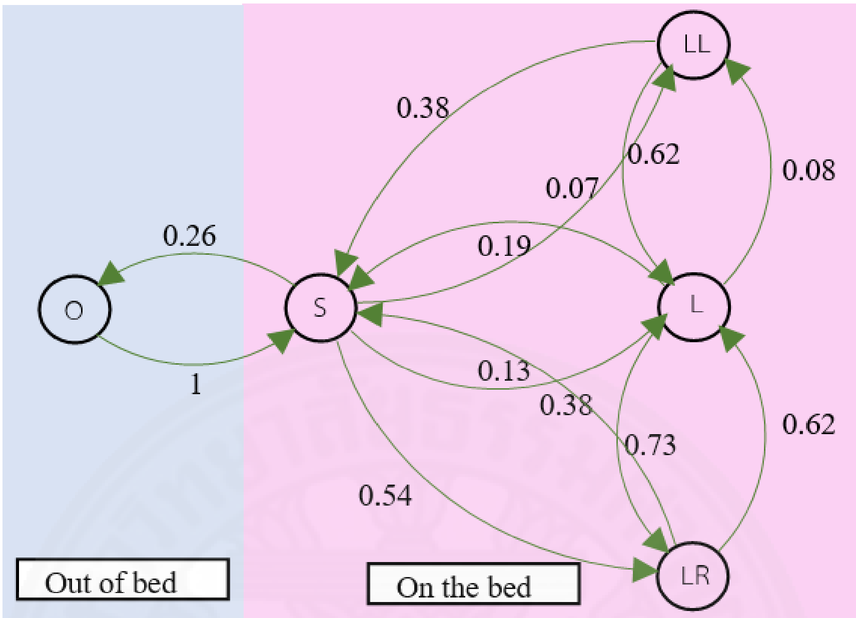


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Figure 4.5 Trasition state of 5 postures

The probability of next posture is shown in Figure 4.5. For example, the next posture from lying down is lying left, sitting, lying right. The probability is 0.08, 0.19, and 0.73, respectively. The probability of the consecutive postures from previous 2 postures and the current one is tabulated in Table 4.3.

Table 4.3 Probability of consecutive postures

P_{i-2}	P_{i-1}	$P(P_i \mid P_{i-1}, P_{i-2})$				
		O	**S**	**L**	**RL**	**RR**
O	**S**	0.439	0	0.122	0.146	0.293
S	**O**	0	1	0	0	0
S	**L**	0	0.333	0	0.048	0.619
S	**RL**	0	0.636	0.091	0	0.273
S	**RR**	0	0.788	0.188	0.024	0
L	**S**	0.238	0	0.143	0.048	0.571
L	**RL**	0	0.111	0.778	0	0.111
L	**RR**	0	0.235	0.716	0.049	0
RL	**S**	0	0	0.375	0.250	0.375

P_{i-2}	P_{i-1}	$P(P_i \mid P_{i-1}, P_{i-2})$				
		O	**S**	**L**	**RL**	**RR**
RL	**L**	0	0.250	0	0.167	0.667
RL	**RR**	0	0.400	0.600	0	0
RR	**S**	0.202	0	0.112	0.022	0.663
RR	**L**	0	0.143	0	0.078	0.779
RR	**RL**	0	0	0.833	0	0.167

4.5 Combination of Neural Network and Bayesian Network

In the very large and unclean dataset, the accuracy decreases from 99.9% in Table 4.1 to 96.84% in Table 4.4. This is because it includes signal errors and unexpected noises. To eliminate the unexpected result of the output posture from the Neural Network model, a Bayesian network is conducted to estimate the likelihood of the consecutive posture. To evaluate the coefficient (α, β) of the weighted arithmetic mean, the value of α and β is varied as tabulated in Table 4.4. When the value of coefficient for Bayesian probability (β) is increased, the accuracy is also increase. The Bayesian Network can improve 0.49% of accuracy with the coefficient ratio of 0.7 and 0.3 for α, and β, respectively. From experiment result, it can be confirmed that Bayesian network affect to eliminate the unexpected consecutive postures.

Table 4.4 Accuracy of the combination of Neural Network and Bayesian network

α	β	Accuracy rate
1	0	96.35
0.7	0.3	96.47
0.5	0.5	96.60
0.3	0.7	96.84
0	1	90.18

Figure 4.6 (a) shows the matrix confusion of 5-postures classification using only Neural Network. The accuracy of sitting posture classifying is low comparing to other. There are noticeably confusion between out of bed and lying right posture because of

similarity of signal pattern. In case of signals in Figure 4.7, the signals of sitting posture are similar to the signals of lying right posture. This is because the subject tends to stay on the right side of a bed. Before getting on or off a bed, the subject sits on the right side of a bed. Then the subject applies pressure on right side of panel sensor. Therefore, the Neural Network may classify wrongly by confusing between these two postures. This case can be solved by applying Bayesian Network approach. For example, Figure 4.8 show signal of movement from out of bed to sitting posture. However, the signal of sitting look similar to lying right posture. From Figure 4.5, the probability of changing posture from out of bed to sitting posture is 1. Therefore, instead of giving the result of lying right posture, our combined model can estimate the correct posture as sitting posture. The results of combined model show in Figure 4.6 (b). Our combined model can improve 2.97% of accuracy in sitting posture. The significant improvement of the estimation of sitting posture is shown in Figure 4.6 (b), comparing to the Figure 4.6 (a) which does not include Bayesian probability. Enhancing the Bayesian probability to the Neural Network model with a proper ratio of combination, our combined model can improve the result of posture estimation due to the confusing errors.

Target class

output	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	96.66	3.34	0.00	0.00	0.00
Sitting	4.68	86.10	0.47	0.70	8.06
Lying down	0.01	0.15	95.65	0.47	3.72
Lying left	0.06	2.47	3.40	94.07	0.00
Lying right	0.00	0.33	1.57	0.00	98.10

(a) Results of coefficient α=1 and β=0

Target class

output	Out of bed	Sitting	Lying down	Lying left	Lying right
Out of bed	96.72	3.25	0.00	0.00	0.02
Sitting	3.91	89.07	0.34	0.44	6.24
Lying down	0.00	0.13	95.99	0.39	3.49
Lying left	0.04	1.56	2.53	93.05	2.82
Lying right	0.00	0.27	1.31	0.00	98.42

(b) Results of coefficient α=0.3 and β=0.7

Figure 4.6. Confusion matrix of 5-postures classification using the combination of Neural Network and Bayesian network

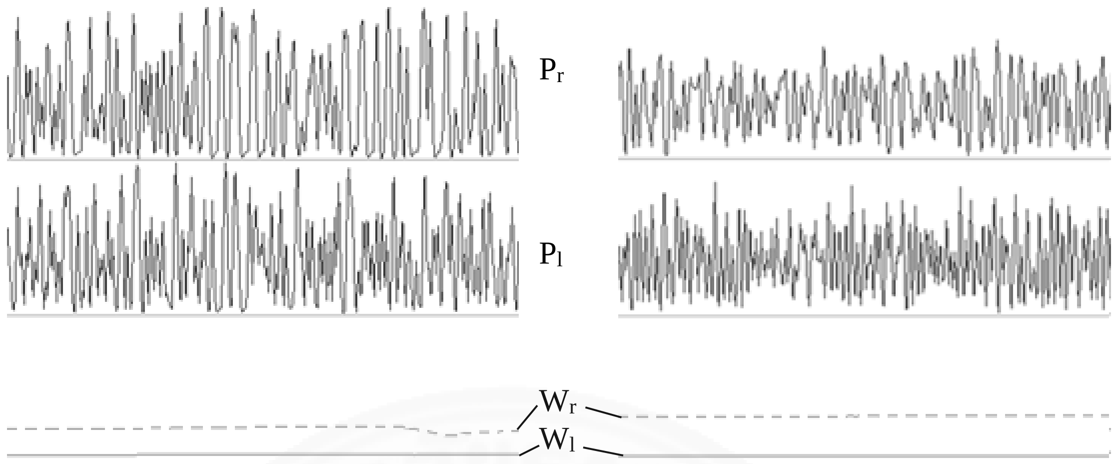

Figure 4.7 Similarity of the signal patterns between sitting posture and lying right posture

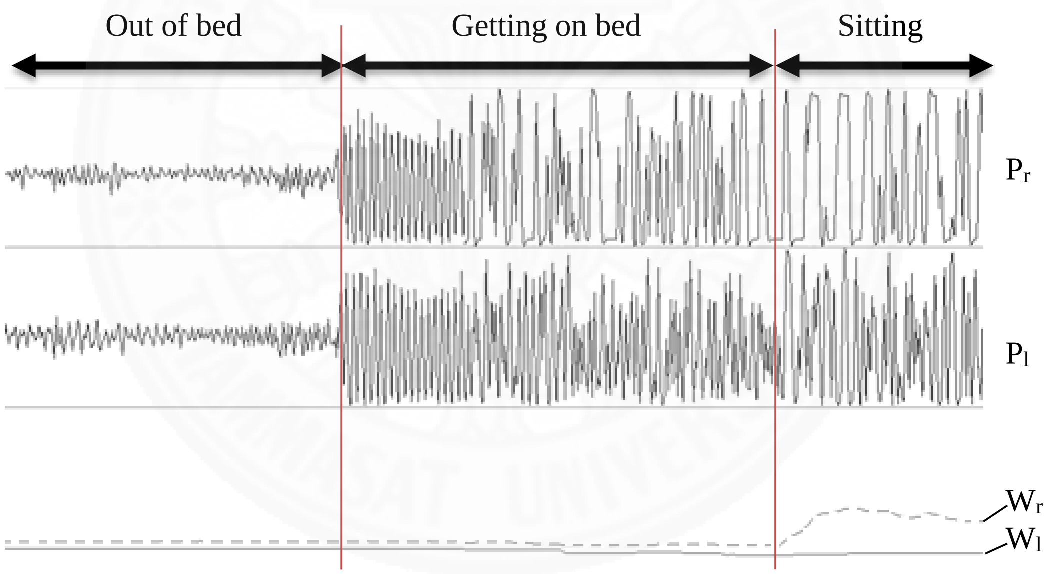

Figure 4.8 Signal pattern of changing posture of out of bed to sitting

Table 4.5 Confusion matrix of 5-postures classification using the combination of Neural Network and Bayesian network with coefficient α=0.3 and β=0.7

	Out of bed	**Sitting**	**Lying down**	**Lying left**	**Lying right**
Out of bed	96.72	3.25	0.00	0.00	0.02
Sitting	3.91	89.07	0.34	0.44	6.24
Lying down	0.00	0.13	95.99	0.39	3.49
Lying left	0.04	1.56	2.53	93.05	2.82
Lying right	0.00	0.27	1.31	0.00	98.42
Recall	96.72	89.07	95.99	93.05	98.42
Precision	96.60	91.80	95.79	87.42	97.35
F-measure	96.63	88.86	95.72	90.63	97.72
Accuracy			**96.35**		

4.6 Comparative Evaluation with Other Approaches

For comparing with other approaches, it is quite difficult to evaluate the performance. This is because there are the difference in datasets, number of posture classification, and equipment. Because other approaches have been done on only sleep posture, we compare accuracy in only 3 postures i.e. lying left, lying down, and lying right as tabulated in Table 4.6. Those of accuracy are calculated by combining all accuracy in each type of postures. For example, in the results of A. Gaddam et al. [8] as shown in Figure 4.9, the accuracy of lying down include all type of supine posture. Also, either lying left or lying right include foetus and log position.

Class	S	S-HOB	S-FL	S-CL	RY	RF	LY	LF
S	100	3.8	0.2	3.2	0	0	0	0
S-HOB	0	95	0	0	0	0	0	0
S-FL	0	0 100	99.8	0	0	0	0	0
S-CL	0	1.2	0	96.8	0	0.2	0	0
RY	0	0	0	0	96.4 99.9	4.8	0	0
RF	0	0	0	0	3.6	95	0	0
LY	0	0	0	0	0	0	97.5	3.5
LF	0	0	0	0	0	0	2.5 100	96.5
Recall	100	95	99.8	96.8	96.4	95	97.5	96.5
Precision	93.2	95	99.8	98.5	95.2	96.3	96.5	96.7
F-measure	96.4	95	99.8	97.6	95.8	95.6	97	96.6
Accuracy				97.1				

Figure 4.9 Confusion matrix of A. Gaddam et al. [8]

Table 4.6 Comparison of 3 postures classification

Ref	Accuracy				# of sensors
	Lying left	Lying down	Lying right	Total	
[8]	100	100	99.9	99.9	2048
[9]	100	98.4	98.8	98.4	1728
[10]	99.9	99.3	100	99.7	280
[12]	100	100	100	100	2048
[13]	99.4	99.9	100	99.8	512
[14]	99.9	99.9	100	99.9	2048
[17]	64.6	93.5	86.2	81.4	16
Ours	**93.1**	**95.99**	**98.4**	**95.8**	**4**

Table 4.7 summarizes the comparison result with other approaches in terms number of postures, accuracy, and number of sensors The performance of our approach is 95.8% which can outperform only 4 from 11 approaches. Our approach needs only four sensors. It is more practical to use fewer number of sensors, low cost, and very handy for installation and maintenance.

Table 4.7 Comparison of sleep posture classification algorithms

Ref	**# of Postures**	**Accuracy (%)**	**Algorithm**	**Type of Sensors**	**# of sensors**
[8]	8	97.1	Binary Pattern Matching	Pressure sensors	2048
[9]	3	98.4	GMM	Pressure sensors	1728
[10]	5	97.7	PCA+SVM	Pressure sensors	280
[11]	3	89.8	Pictorial Structure	Pressure sensors	8192
[12]	5	98.1	HoG+DNN	Pressure sensors	2048
[13]	4	99.7	SVM	Pressure sensors	512
[14]	5	97.7	PCA	Force Sensing Array	2048
[15]	6	83.5	Raw Data + SVM	FSR Sensors	56
[16]	9	94.05	Joint feature extraction and normalization +SVM+PCA	FSR Sensors/Video	60
[17]	3	81.4	Kurtosis+Skewness	FSR Sensors	16
[18]	5	98.4	SVM+RBF kernel	CC-electrodes	12
Ours	**3**	**95.8**	**NN+Bayesian propability**	**Pressure sensors/piezoelectric**	**4**

Chapter 5
Conclusions

This study present bed posture classification for elderly care. For preventing an accident around a bed, the monitor system needs a high accuracy to detect the postures on a bed. The neural network is adopted to classify 5 different postures. The normalized signal data can eliminate the bias of weight effect and the difference of type of sensors. In this study, neural network is adopted to classify 5 different postures. Also, the accumulated signal data in one second time slot as 120 inputs can improve performance and solve confusion between sitting and out of bed posture. The accuracy of 120 inputs with normalized signal data is better than other 3 types of input feature i.e. 4 inputs, 4 inputs with normalized signal data, and 120 inputs. In the large and unclean dataset, the accuracy decrease significantly. To improve the performance of a neural network model, Bayesian network is used to eliminate unexpected results. In proper weight ratio of combination of neural network and Bayesian network, it can improve 2.97% in sitting posture. Our approach achieve an accuracy of 94.65% with the coefficient ratio of 0.7 and 0.3 for Neural Network and Bayesian network probability, respectively. From the results, Bayesian network probability is effective parameter for bed posture classification. Comparing to previous approaches, our approach needs only 4 sensors without losing much in performance. Although other approaches give a very promising result, they needs a large number of sensors. Hence, it can be concluded that our approach can perform a high accuracy in bed posture detection and require the minimum number of sensors.

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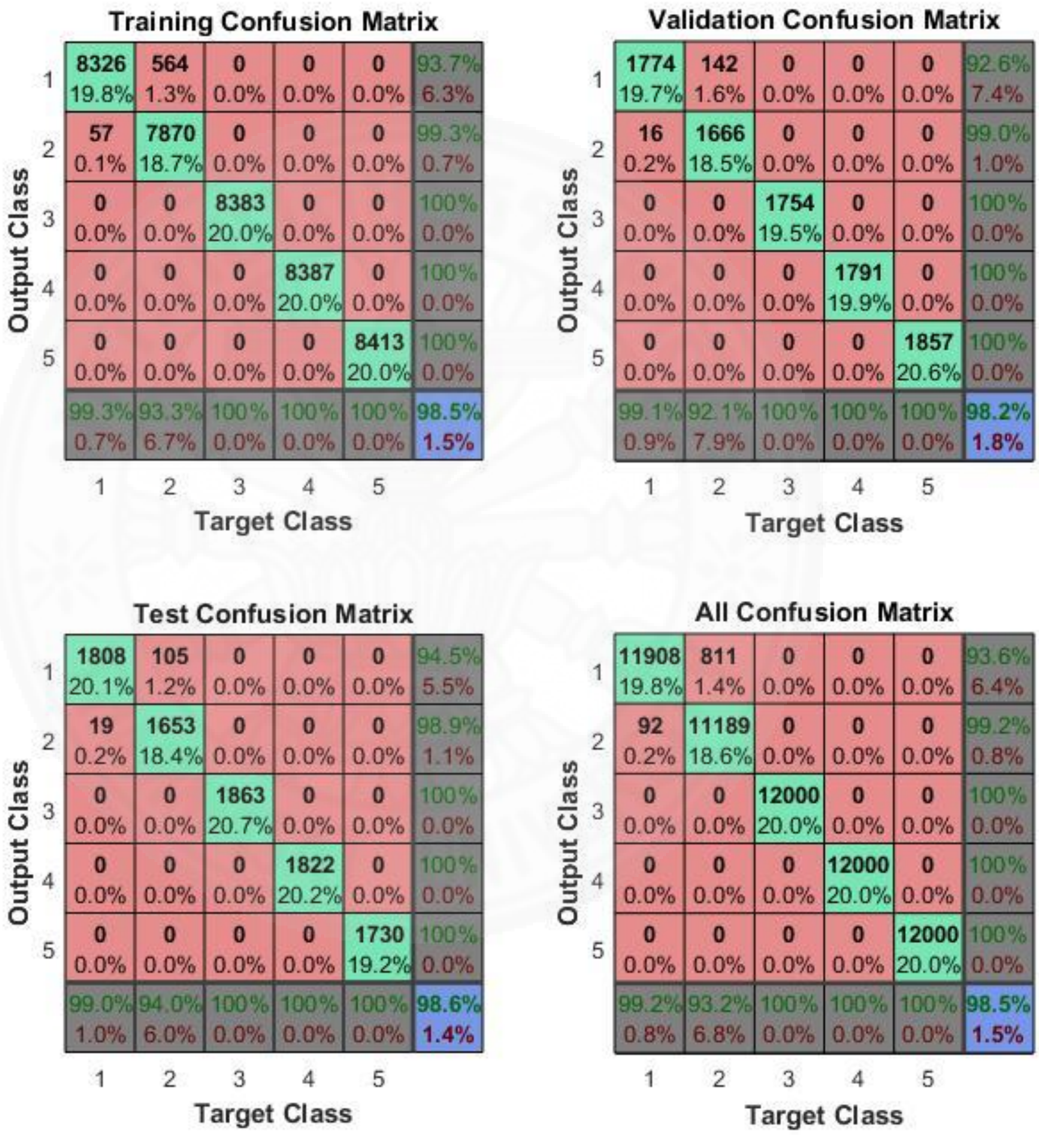
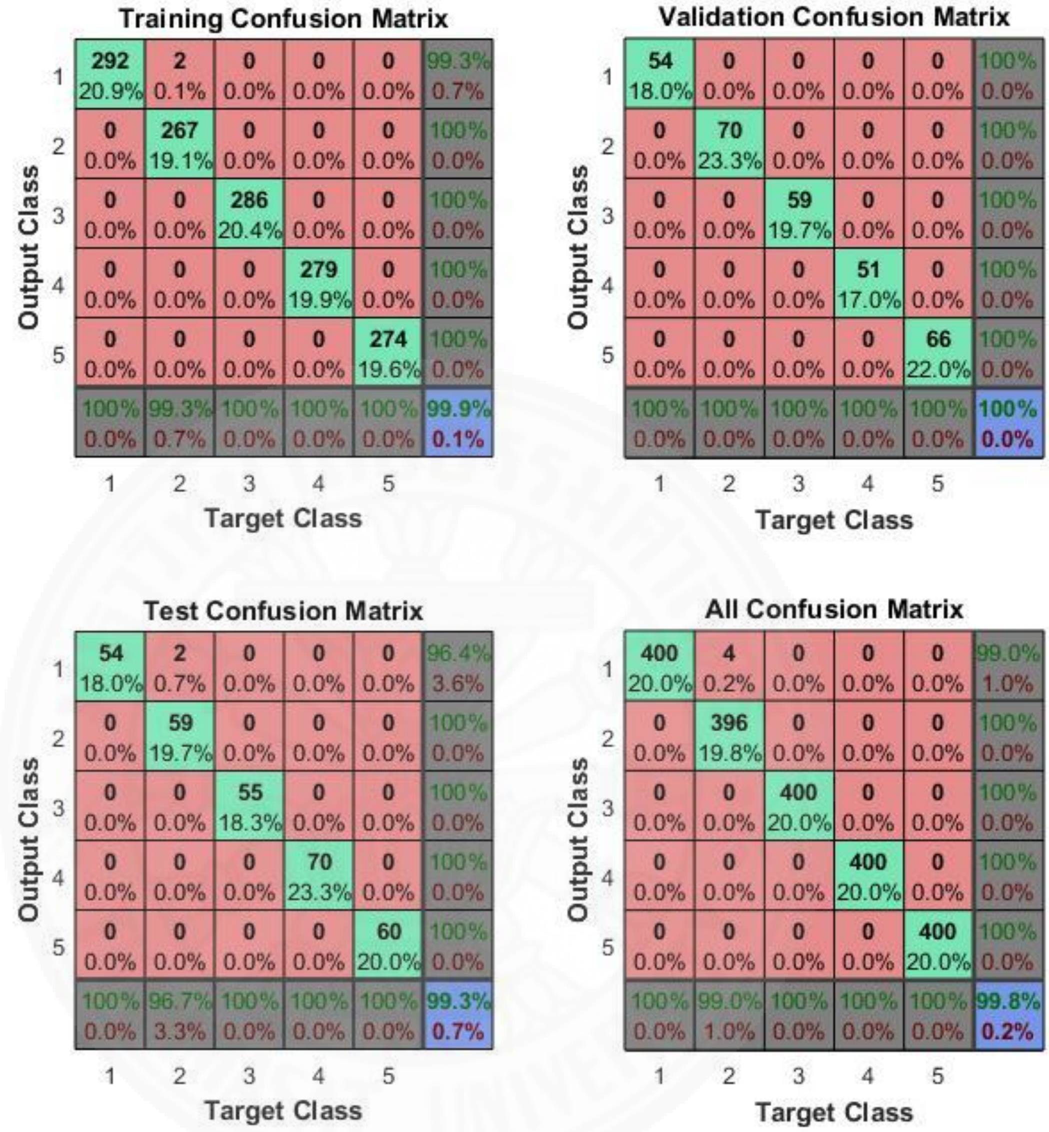
Appendices

Appendix A

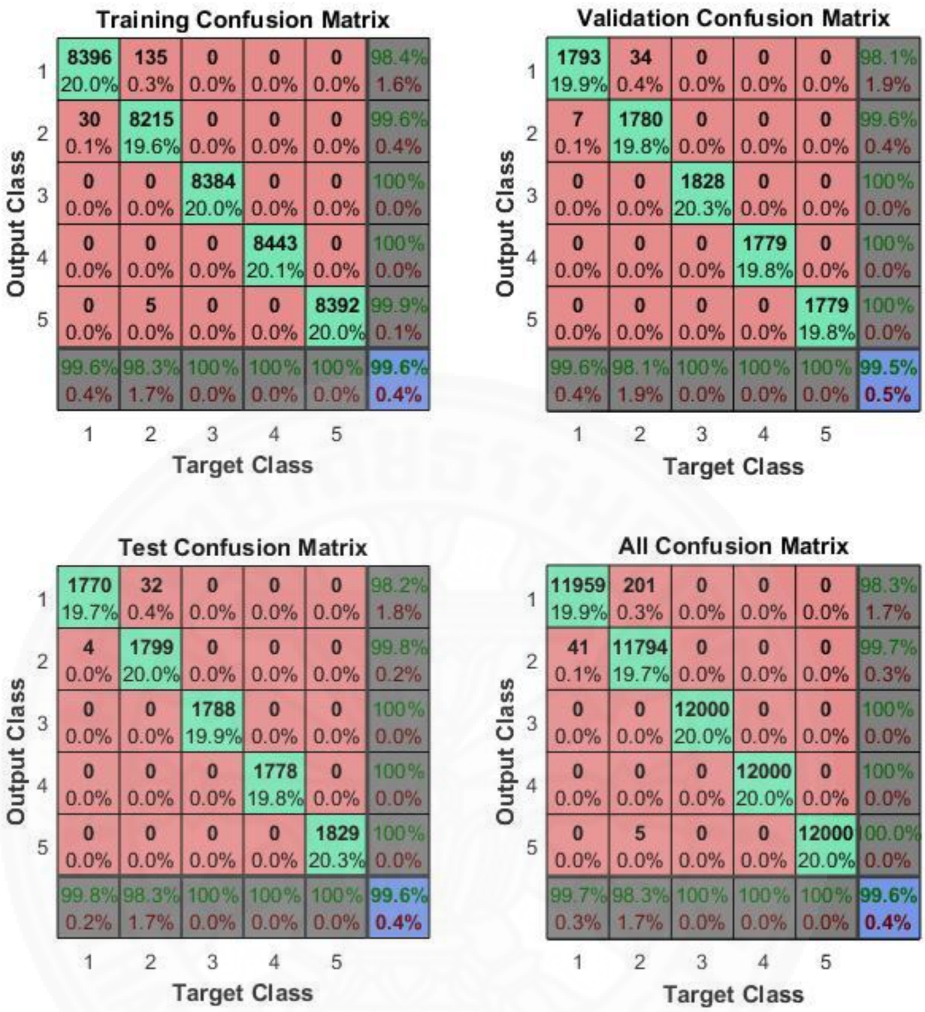
Experimental result



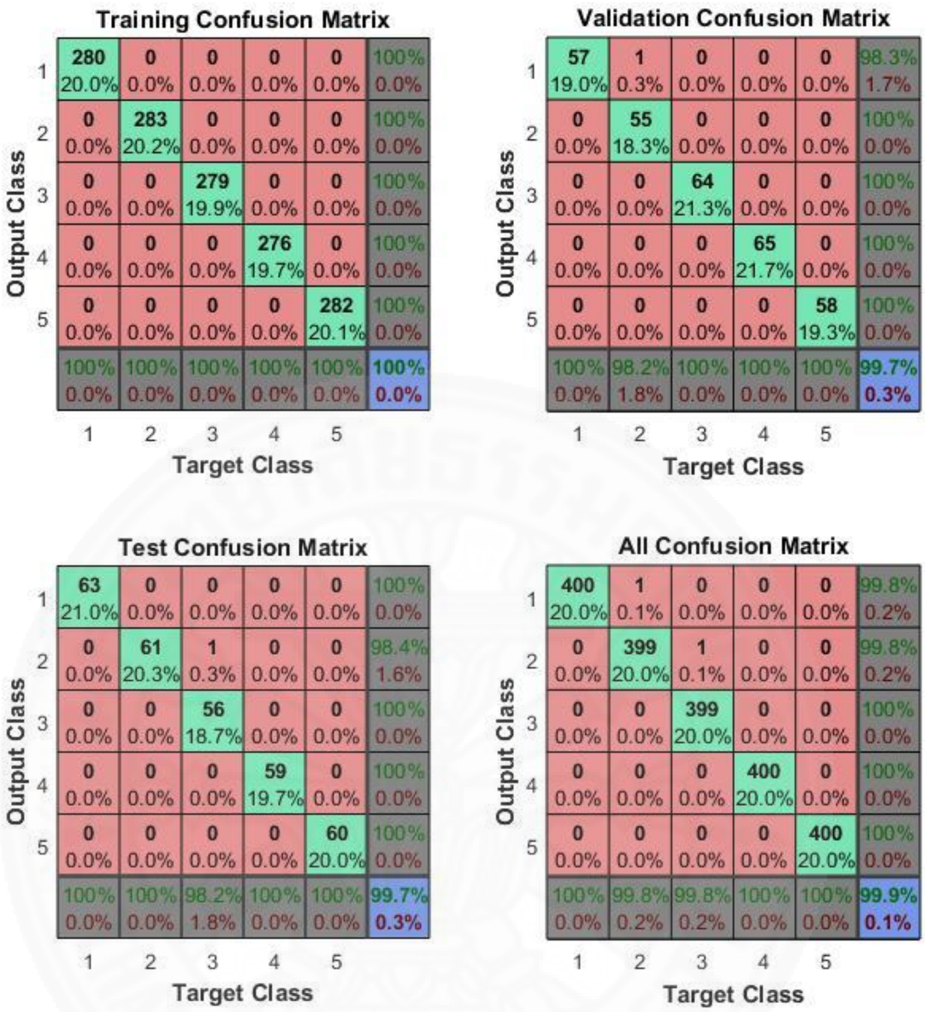
Confusion matrix of posture classification using 4 inputs of subject A



Confusion matrix of posture classification using 120 inputs of subject A



Confusion matrix of posture classification using 4 inputs with normalized signal data of subject A



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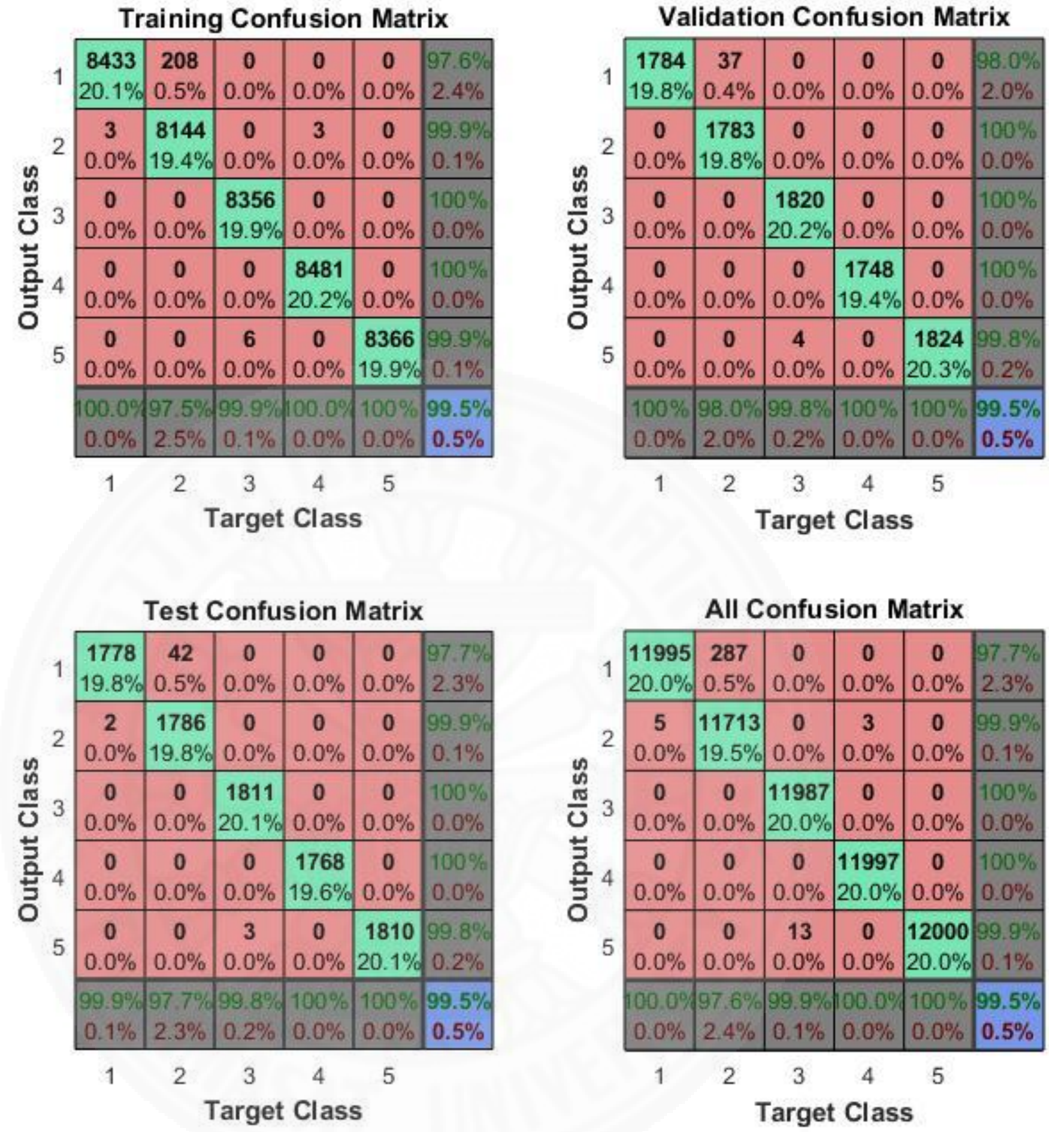
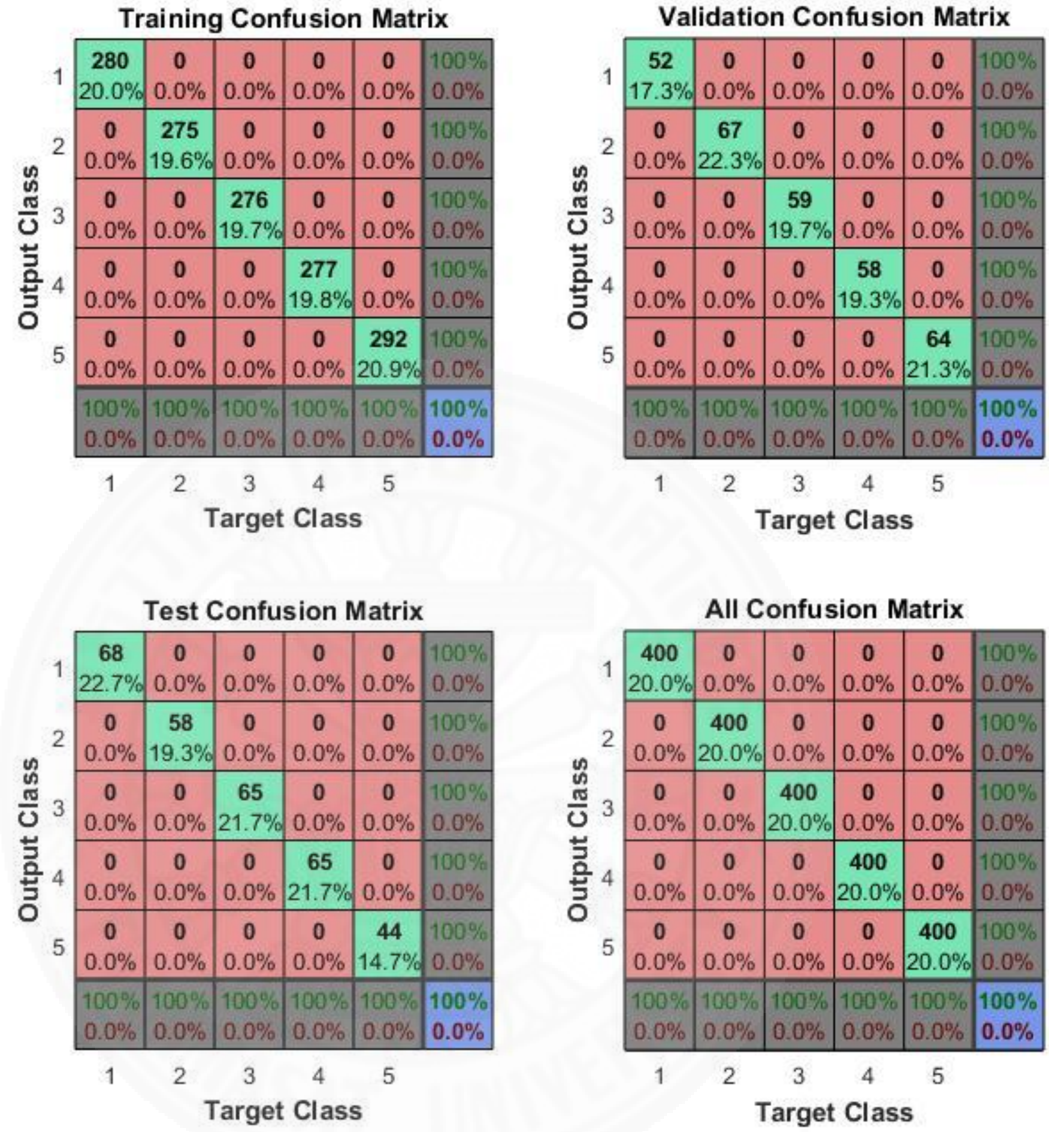
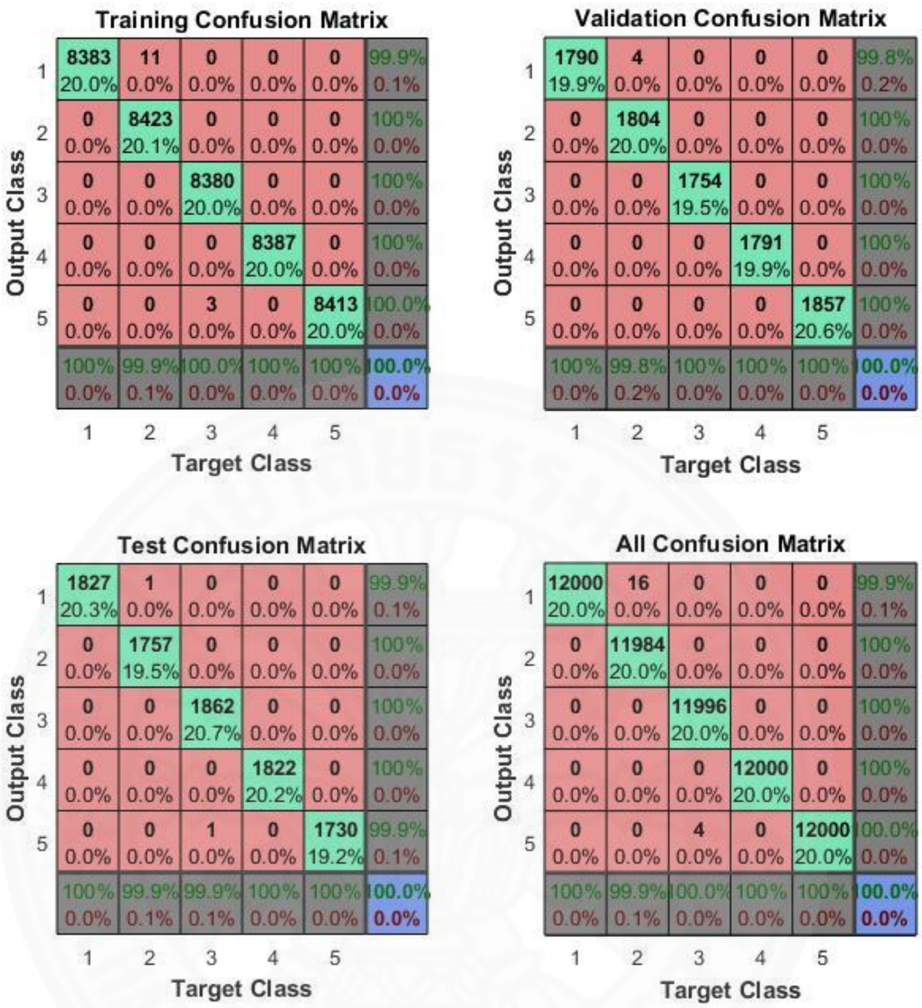


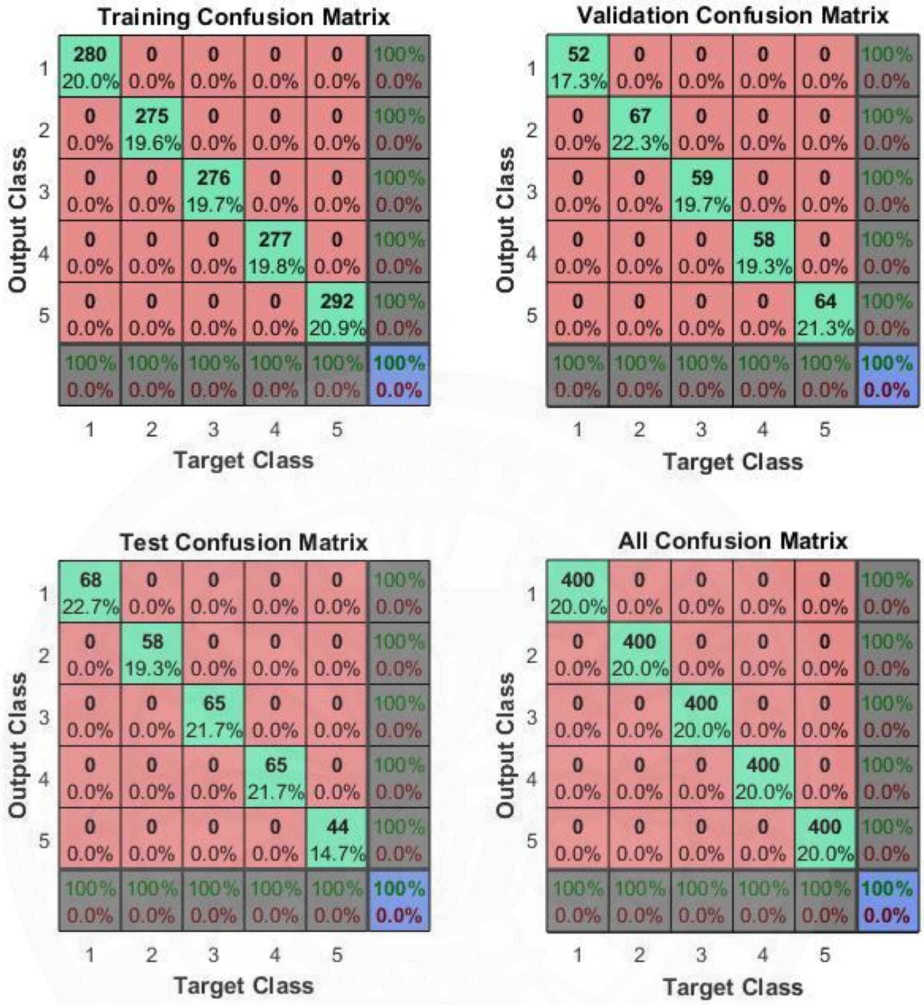
Confusion matrix of posture classification using 4 inputs of subject B



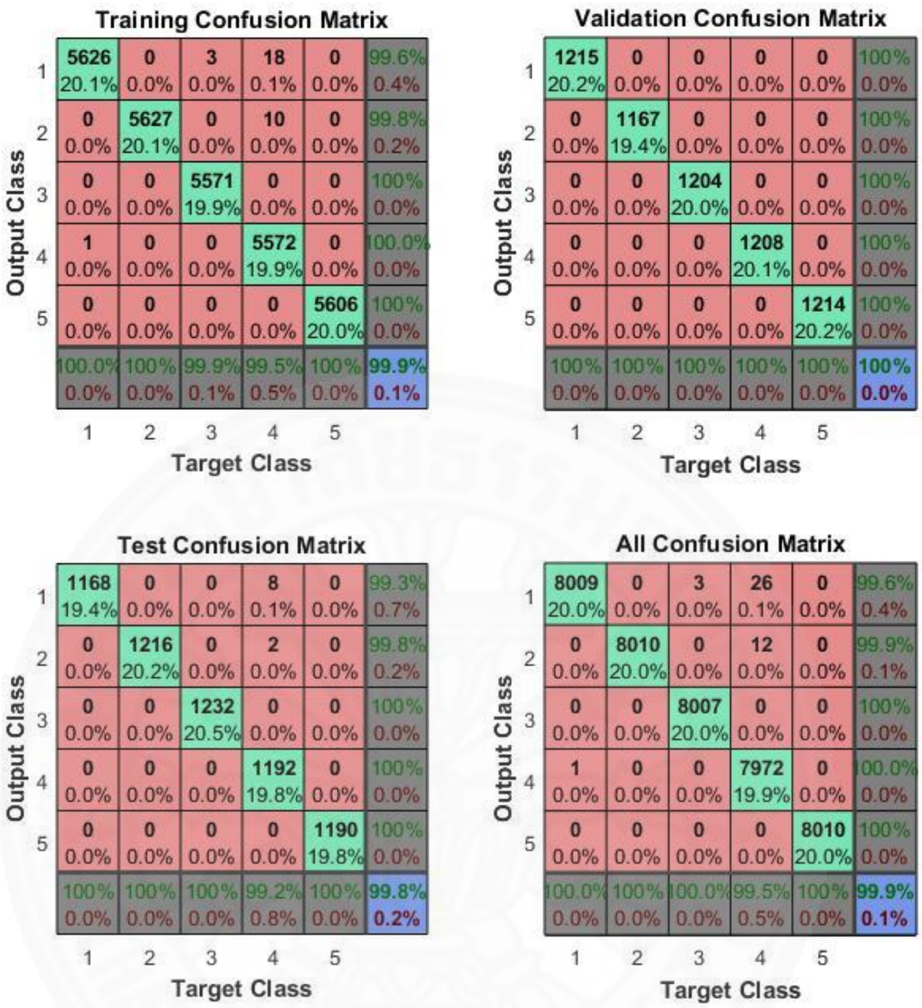
Confusion matrix of posture classification using 120 inputs of subject B



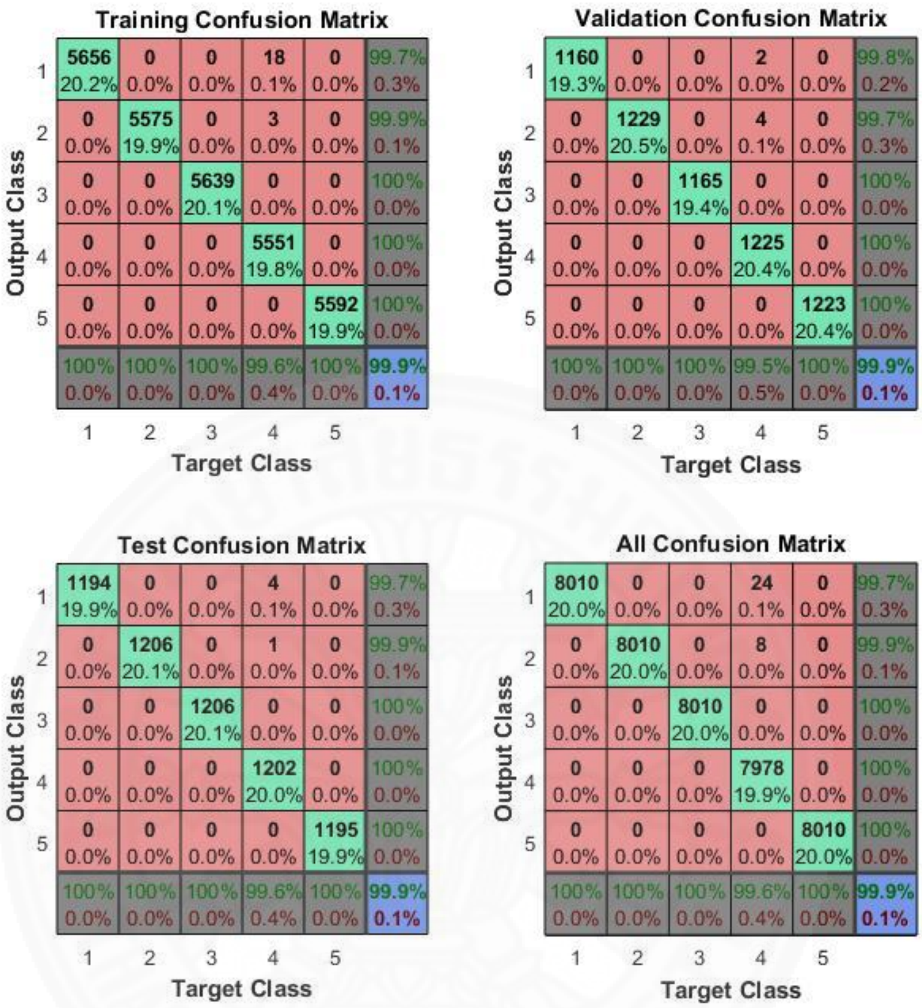
Confusion matrix of posture classification using 4 inputs with normalized signal of subject B



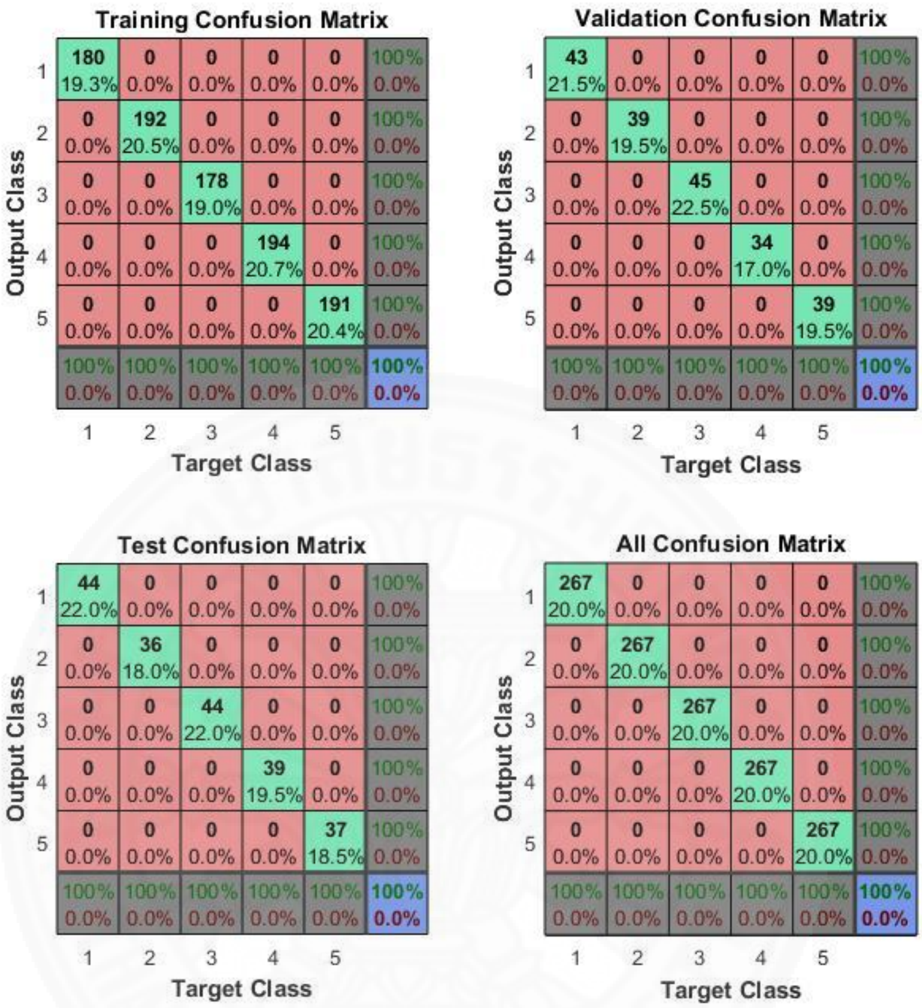
Confusion matrix of posture classification using 120 inputs with normalized signal of subject B



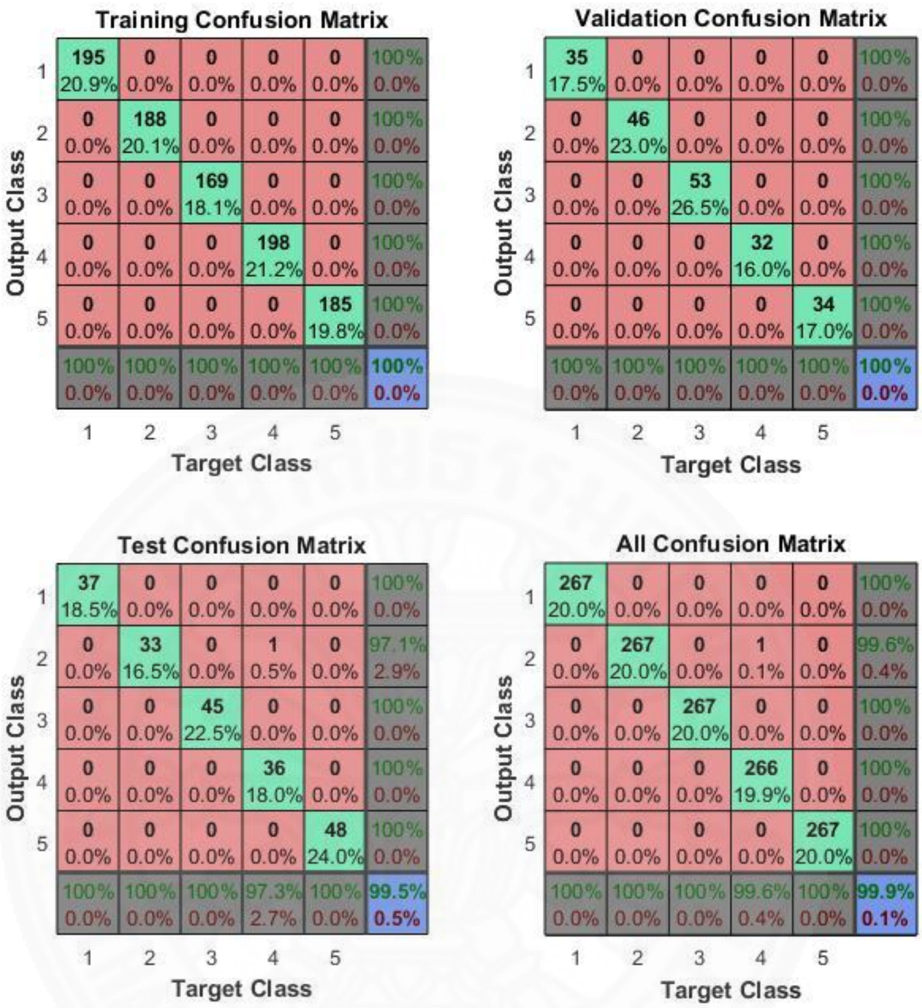
Confusion matrix of posture classification using 4 inputs of subject C



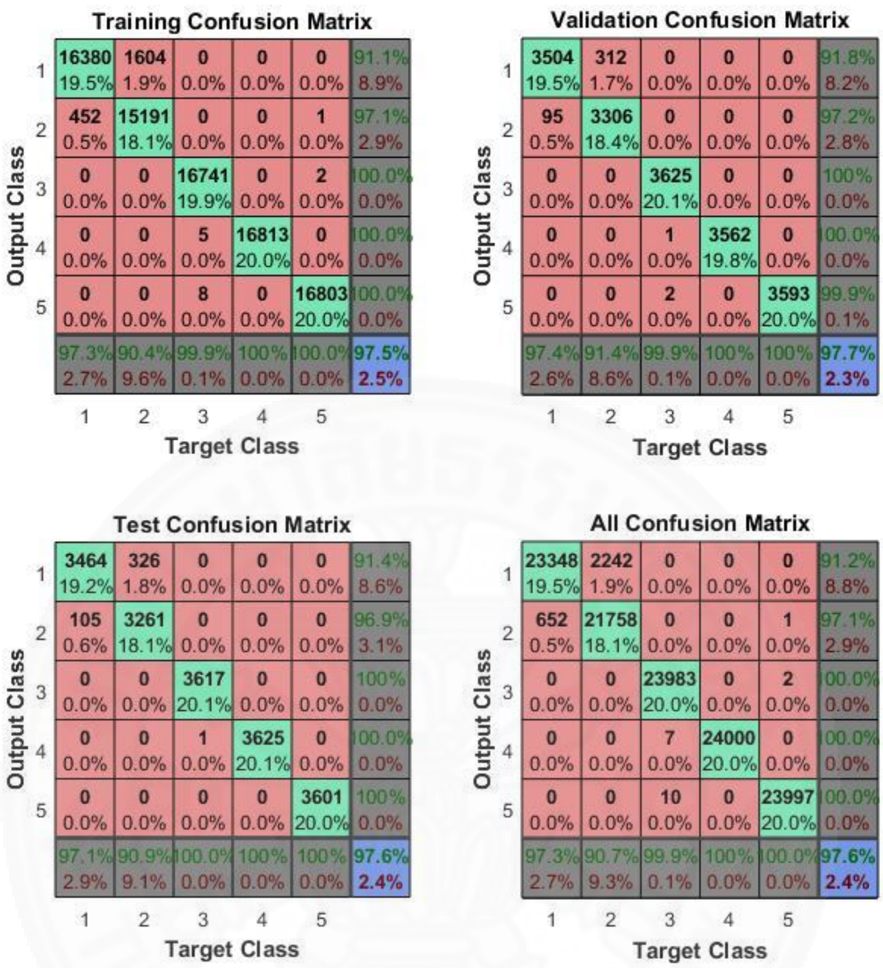
Confusion matrix of posture classification using 4 inputs with normalize of subject C



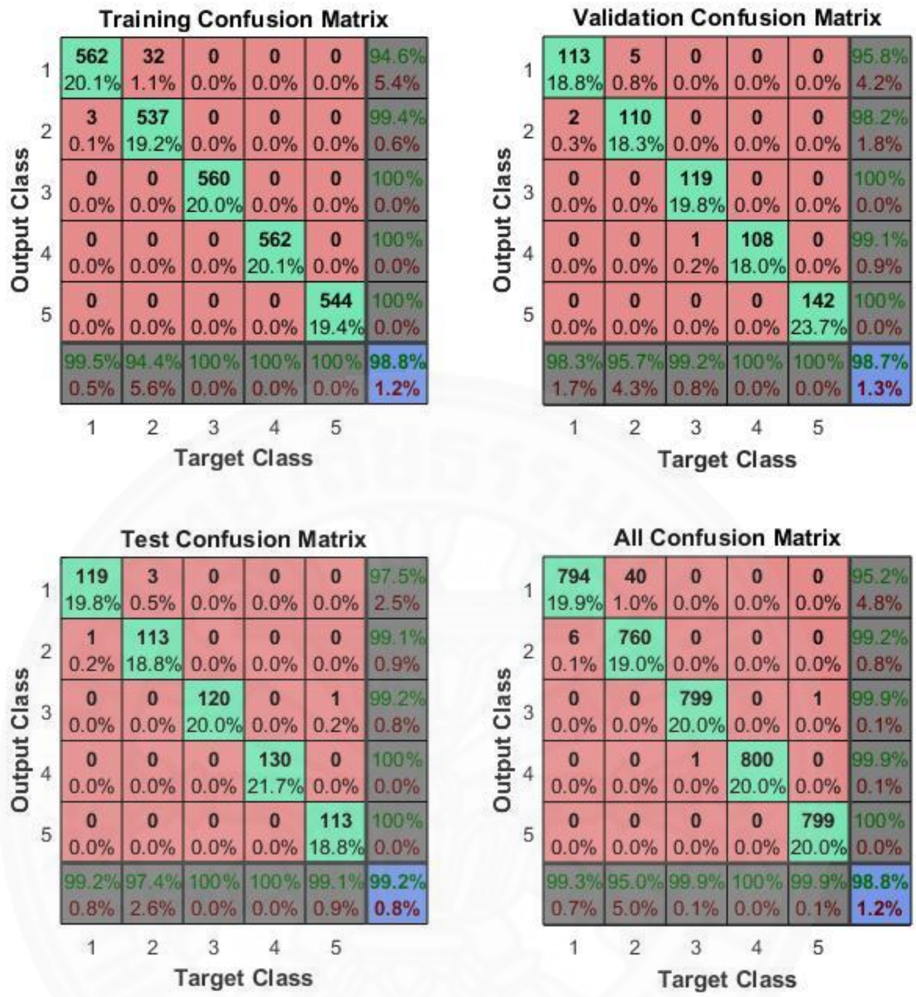
Confusion matrix of posture classification using 120 inputs of subject C



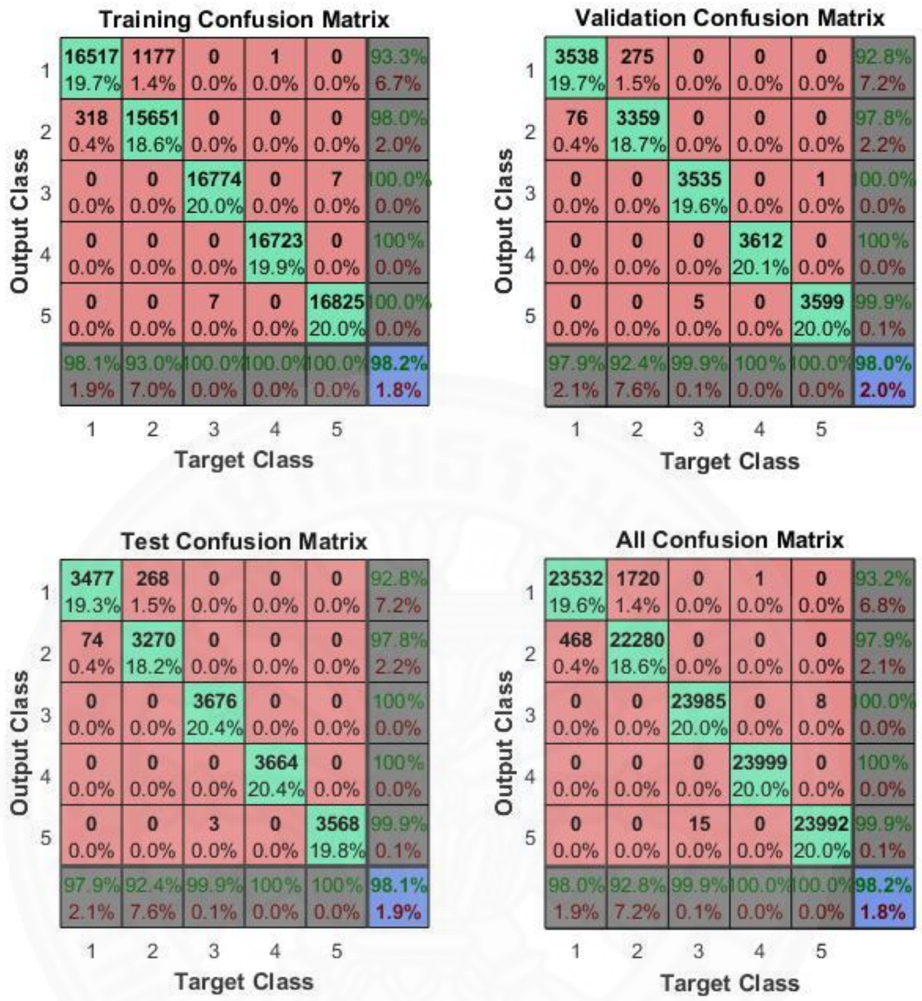
Confusion matrix of posture classification using 120 inputs with normalized signal of subject C



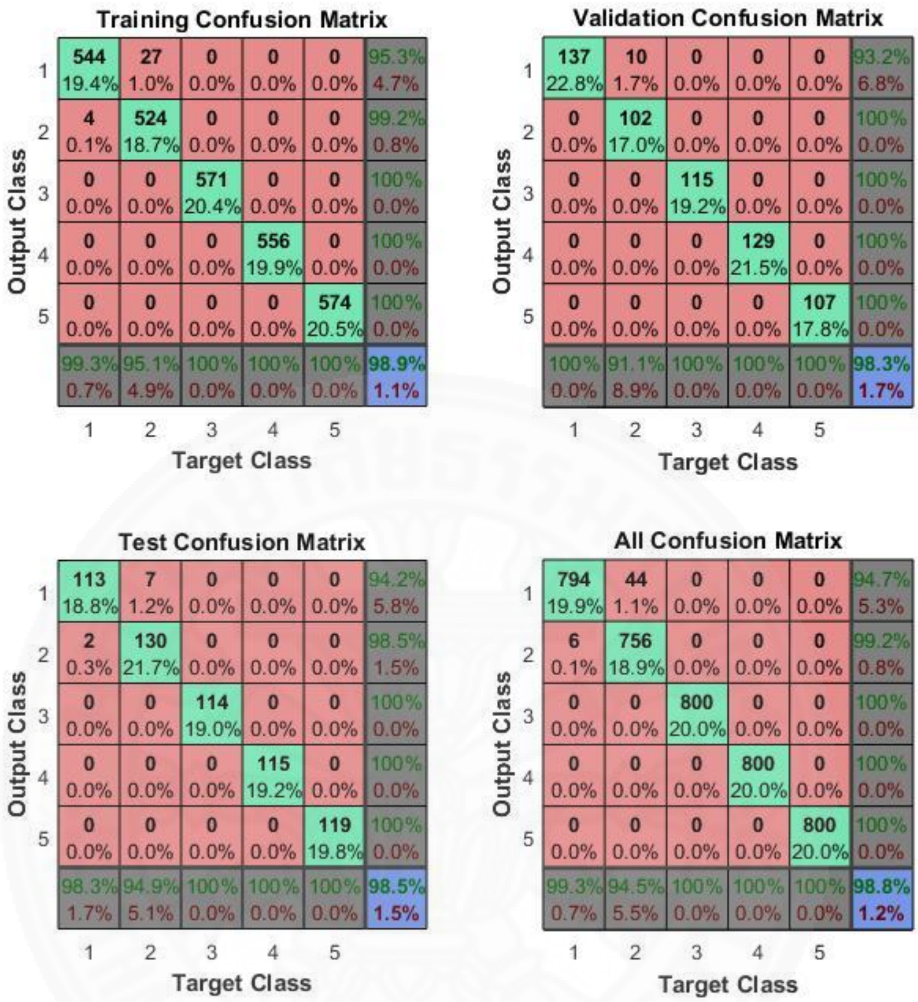
Confusion matrix of posture classification 4 inputs using of subject A and B



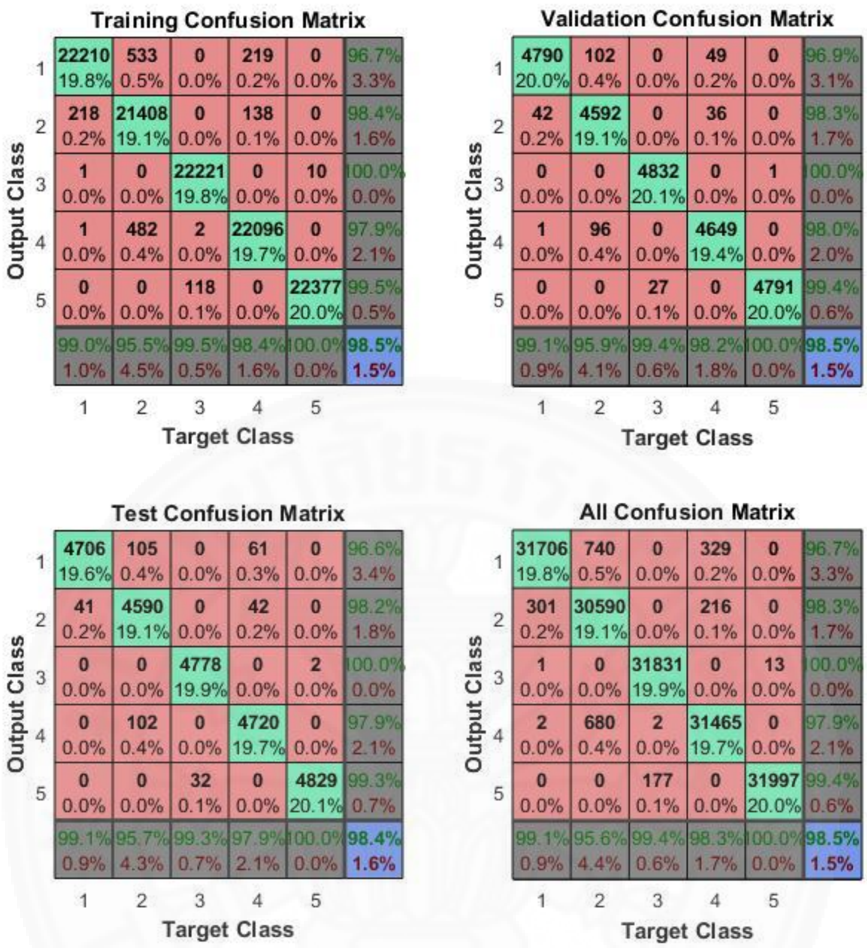
Confusion matrix of posture classification using 120 inputs of subject A and B



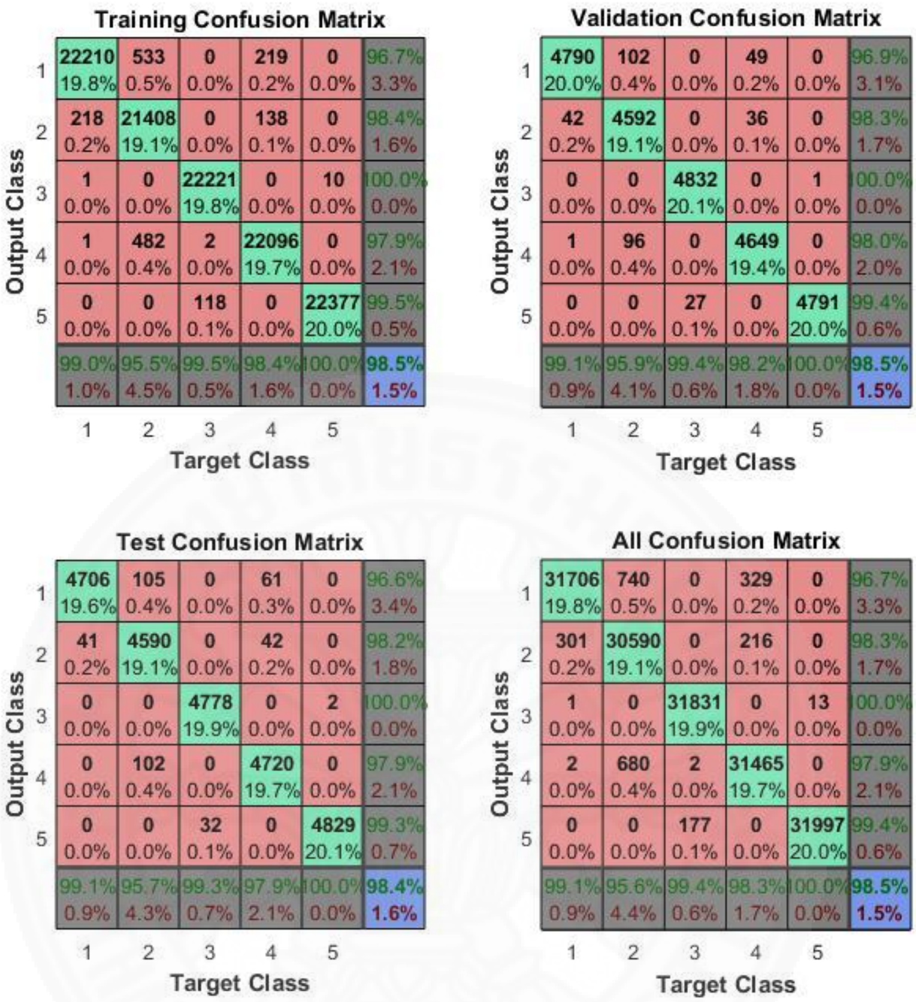
Confusion matrix of posture classification using 4 inputs with normalized signal data of subject A and B



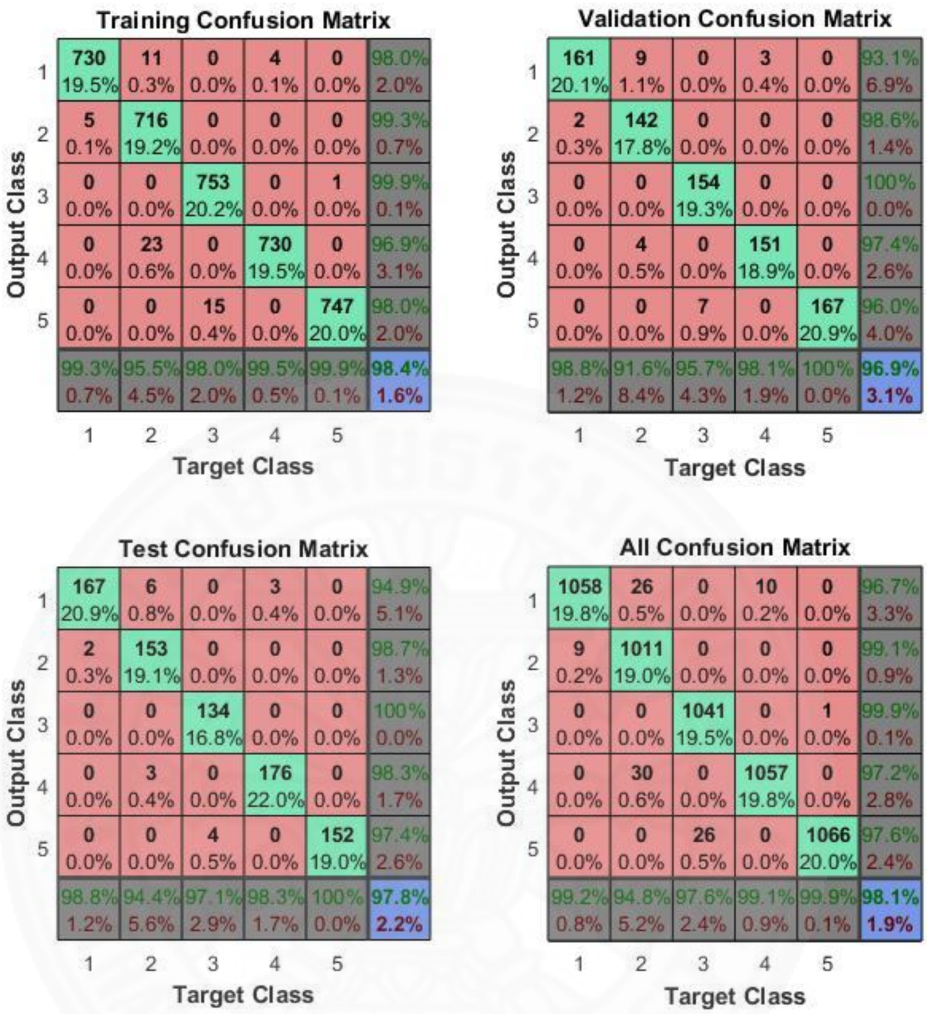
Confusion matrix of posture classification using normalized 120 inputs of subject A and B



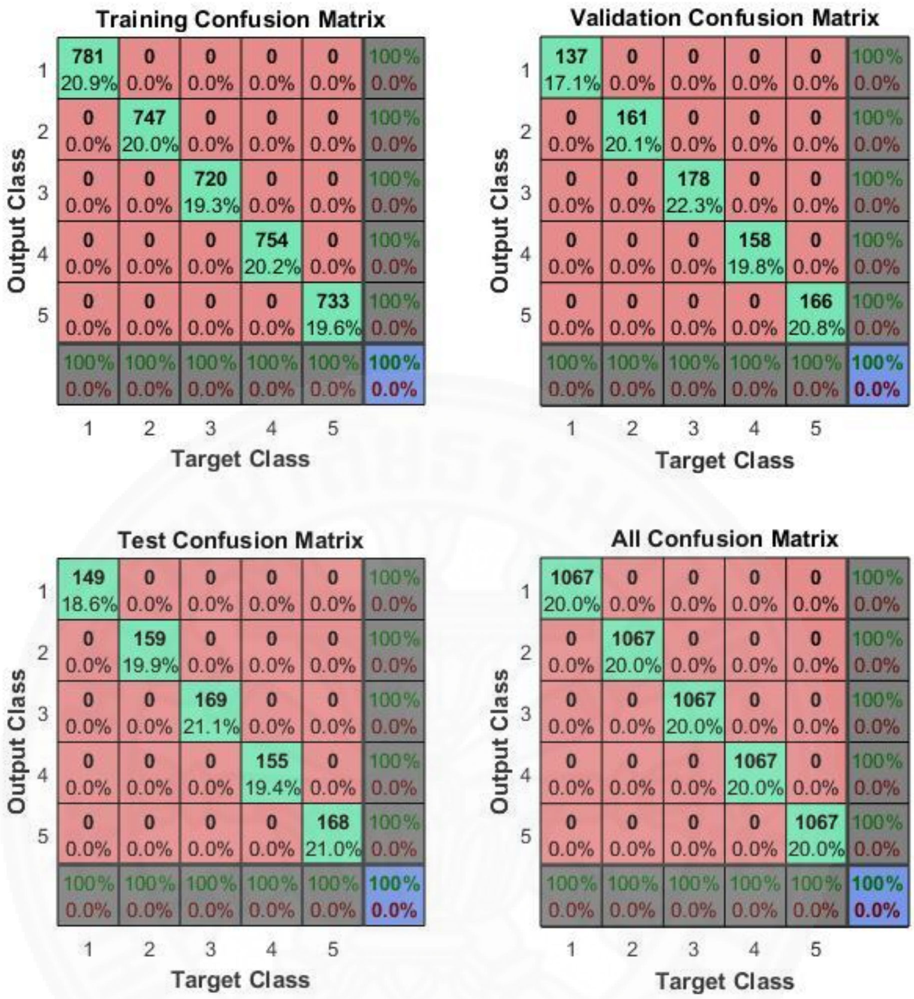
Confusion matrix of posture classification using 4 inputs of combination of two rooms



Confusion matrix of posture classification using 4 inputs with normalized signal of combination of two rooms



Confusion matrix of posture classification using 120 inputs of combination of two rooms



Confusion matrix of posture classification using 120 inputs with normalize signal of combination of two rooms