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基於加速度計之雞隻動作型態識別與活動力估測系統之研究

Development of Accelerometer-based System for Activity Pattern Recognition and Vitality Estimation of Chicken

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本論文係 施銘榮 君（R97631034）在國立臺灣大學生物產業機電工程學系、所完成之碩士學位論文，於民國 100 年 6 月 21 日承下列考試委員審查通過及口試及格，特此證明

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系主任、所長 周瑞仁（簽名）

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摘要

本研究的主要目的為建立一套雞隻動作型態識別與活動力估測之系統。根據裝置在雞隻上的加速度計訊號，來判斷其動作型態，包括走路、啄食、起身與坐下、休息和其他等動作；活動力則以加速度訊號的能量來評估。研究架構分成資料擷取、處理與分析，動作型態識別與活動力估測。資料擷取部分主要整合微機電式三軸加速度計、ZigBee 元件與電腦成一無線加速度紀錄器，將此三軸加速度記錄器背負在雞隻的背部，以量測活動的加速度訊號，透過 ZigBee 將加速度訊號傳回電腦端儲存，同時以 DV 拍攝活動紀錄；在資料處理與分析方面採用內插法，並將加速度訊號對比相對應的影像資訊，找出不同動作之特徵，本研究採用之特徵，包括三維訊號兩兩間之相關係數、中位數、四分位數間距、峰值數目、頻譜能量、頻譜熵，小波不同頻段之峰值、能量、主頻率等。動作識別部分以動作特徵建立並測試了 63 種分類模型，以建模資料進行十疊交叉驗證法(10-fold cross-validation)，貝式(Bayesian)網路分類器的辨識準確率為 86.1%；以測試資料測驗模型，同種(Homogeneous)資料測試結果，貝式網路的辨識準確率為 74.42%；異種(Heterogeneous)資料測試結果，貝式網路的辨識準確率為 72.10%，顯示貝式網路之辨識結果較為強健，適合應用在雞隻的動作型態識別。活動力估測係從雞隻活動加速度訊號求得活動資訊，使用小波轉換、活動框架偵測與訊號能量等方法，得到活動框架的平均功率，用以評估雞隻的活動情形與健康程度，達到疾病預警的目的。

關鍵字：活動力估測、動作識別、加速度、貝式網路分類器、小波轉換、平均功率

Abstract

The purpose of this paper is to design a system to recognize activity pattern and estimate vitality of chicken. The activity to be recognized includes walk, peck, stand-up and sit-down, rest, and other, etc. The vitality is estimated by energy of acceleration signal. The framework of this study consists of data collection, processing and analysis, activity pattern recognition, and vitality estimation. On data collection, a Wireless Acceleration Logger is designed by integrating MEMS 3-axis accelerometer with ZigBee devices. The three-axis acceleration signals is collected by attaching the Acceleration Logger on the back of chicken, and the collected acceleration signals will be sent to computer by ZigBee. At the same time, a digital video camera is used to record the behavior of chickens. For data processing and analysis, interpolation and wavelet method are used for signal processing. By comparing acceleration signals with the corresponding video clips, the features of various activities could be determined and acquired for further analysis. The features used in this study are correlation coefficients between signals in different axes, median, interquartile range, peak, spectrum energy, spectrum entropy, principal frequency of wavelet bands, amplitude of principal frequency of wavelet bands, and energy of wavelet bands. As of activity recognition, 63 models have been constructed and validated. The accuracy of Bayesian network is

86.10% by 10-fold cross-validation. However, at testing stage, the accuracy of Bayesian network on testing homogeneous dataset is up to 74.42%; the accuracy of Bayesian network with heterogeneous dataset is around 72.10%. The result shows that Bayesian network has the best prediction capability for chicken activity recognition than other models and is also more robust. On vitality estimation, vitality index is estimated from acceleration signals of chicken through wavelet transform, activity frame detection, and the average power of activity frames. The health condition of chicken could be evaluated to achieve the purpose of sickness early warning based on the vitality information.

Keywords: vitality estimation, activity recognition, acceleration, Bayesian network classifier, wavelet transform, average power

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Chapter 1 Introduction

Chicken is one of the most important sources of meat, and it is protein-rich, low fat and rich in amino acids. The production value of the chicken industry ranks second in the domestic livestock and poultry in Taiwan, and it is only next to swine industry (Council of Agriculture, Executive Yuan, 2009). The production value of chicken is greatly reduced by avian influenza or other diseases, particularly in December 2003. Therefore, the study aims to develop a system to facilitate the management of chicken house by early warning on the decay of chicken health condition.

To avoid disease spreading out in a chicken house, the health of chickens based on their behavior or vitality should be frequently monitored. The vitality could be estimated by their motion in terms of moving distance in 10 minutes (Chen, 2006) or acceleration (Green *et al.*, 2009). In previous study, some researchers use cameras to capture the motion and make judgment (Chen, 2006; Wang *et al.*, 2010). Besides, activity patterns provide useful information to analyze vitality in more details. The human acceleration data have been widely studied for the activity pattern recognition of human (Bao and Intille, 2004). To be applied in animals, the methods still have to be further investigated.

In this study, the activity pattern and vitality of chicken are investigated for evaluating the health condition of chickens by developing a system with accelerometers, wireless transceiver devices and analysis algorithm.

The rest of this thesis is organized as follows: Related literature will be discussed in Chapter 2. Then the acceleration signal acquirement, activity recognition and vitality estimation method are presented in Chapter 3. In Chapter 4, the result of activity pattern recognition and vitality estimation will be discussed and illustrated. Finally, the conclusion is given in Chapter 5.

Chapter 2 Literature Review

The animal science has being developed for more than hundred years. In this field, research on animal behavior gradually draws attention. According to the definition of animal behavior by Animal Behavior Society (ABS), “animal behavior is the scientific study of everything animals do” (ABS, 2006).

In animal behavior study, observing what animals do is the most basic step. The oldest method is to observe and record information of animals by human. Droege and Sauer (1989) reported the project of a survey on North American breeding bird, beginning in 1966, and the project was carried out mainly human observation. The method has two defects, first one is the animal information will be lost due to human neglect. Second one is data only recorded while animals appear before observers.

During the last several decades, there has been a rapid growth of mechatronic technology. Therefore, people have been trying to utilize new technology, like radio-telemetry and loggers, to obtain information on animal behavior. The advantages of using such a technology are as follows: (1) It can reduce human error and interference on animals. (2) The information of animal can be acquired automatically.

Currently, people try to use radio-telemetry technology to study animal behavior. The radio-telemetry method can acquire information and location of animal within sensing range. Ostfeld (1986) used radio-telemetry method to investigate territoriality and mating system of California Voles. Severinghaus (2000) used radio-telemetry to study territoriality of Lanyu Scops Owl.

Bressers (1993) investigated automatic oestrus detection for group housed sows in 1993. He hung a 3-axis accelerometer neck collar on sows. Two parameters, which are mean amplitude and the number of signal passing a threshold, are used to differentiate pre-oestrus and oestrus conditions.

Over the past two decades, the trend of using data-logging devices appended on animal is more clear (Muramoto *et al*., 2004; Ropert-Coudert and Wilson, 2005), and the logging technology have improved the research method on animal study. The issues about Bio-logging were officially introduced on International Symposium on Bio-logging Science in 2003 (Naito *at el*., 2004). The definition of Bio-logging is "the theory and practice of logging and relaying of physical and biological data using animal-attached tags" (Hooker *et al*., 2007). Some people studied penguins via loggers to acquire its activity information including speed (Wilson and Bain, 1984), acceleration, and diving depth (Yoda *et al*., 1999; Yoda *et al*., 2001). Some researchers used logger to study flight, foraging, and diving behavior of birds (Ropert-Coudert and Wilson, 2005; Pelletier *et al*., 2007).

Recently, many advances have been made in the area of automatic recognition. Among these domains, using acceleration to recognize daily activity of animal has been rapidly developed. Bao and Intille (2004) studied human activity recognition by using accelerometers which are worn on thigh, ankle, arm, wrist, and hip. The goal in their study is aiming to recognize 20 daily activities. Activity features used in the study are mean, spectrum energy, spectrum entropy, and correlation between signals in different axes. They tested four models which consist of Decision Table, IBL, C4.5 decision tree, and Naive Bayesian. The test shows the C4.5 decision tree classifier performed best. The recognition accuracy achieved 80% on a variety of 20 daily activities at model validation stage.

Bayesian network, developed based on a rigorous probability approach, is particularly good at capturing relationships between variables, handling hundreds of variables with noise data, describing processes composed of locally interacting elements, providing causal influence. Therefore, the model is a suitable solution for problems involving reasoning under uncertainty, and it has shown promise in many applications (Friedman *et al*., 2000; Myers *et al*., 1999; Pearl and Russell, 2002; Yu *et al*., 2004).

Previous research compared the ability of classification for Bayesian network classifier with other models, and the results in average end in a draw or are even better (Langley *et al.*, 1992; John and Langley, 1995; Baesens *et al*., 2004; Pernkopf, 2005).

Langley *et al*. (1992) performed a comparison among Bayesian network, C4, and frequency-based classifiers on datasets from the databases of 5 domains. The result shows Bayesian network classifier has best performance in 4 domains.

John and Langley (1995) compared two types of Bayesian network classifier, which are Naïve Bayes and Flex, with C4.5 Decision Tree classifier. They tested those classifiers on the datasets from databases of 11 domains, and the result with Bayesian network classifier is the best in 8 domains.

Baesens *et al*. (2004) used Bayesian network classifiers for identifying the slope of the customer-lifecycle of long-life customers. They compared 5 types of Bayesian network classifier, which are Naïve Bayes, TAN, CL multinet, GBN, and GBN multinet, with C4.5, C4.5reles, LDA, and QDA classifiers. In average, Bayesian network classifiers perform better in predicting future customer evolution.

Pernkopf (2005) compared Bayesian network with k-NN classifier on datasets from the databases of 8 domains. The Bayesian network classifier out-performed in 5 domains, so they prefer to choose Bayesian network classifier.

In this study, a data-logger is developed to be attached on the back of chickens to acquire acceleration data for the activity pattern recognition and vitality estimation of chickens. In chapter 3, the development of our system will be described in detail.

Chapter 3　Materials and Methods

This chapter is arranged as follows: In section 3.1, the overview of approach developed in this study will be illustrated. In section 3.2, the acceleration logger system is introduced. Then how the acceleration logger system is used to collect and pre-process acceleration data. Section 3.3 will illustrate the recognition process of activity patterns. Finally, the vitality estimation method will be presented in section 3.4.

3.1 Approach Overview

The flowchart of approach employed in this study is shown in Fig. 3-1. The objective of this chapter is to develop a system to evaluate the health condition of chickens by recognizing activity patterns and estimating the vitality of chickens. The whole processes to achieve our objective are based on the analysis of acceleration signals. Therefore, an acceleration wireless logger system is necessary to be developed for acquiring acceleration signals. The detailed descriptions will be given in following sections.

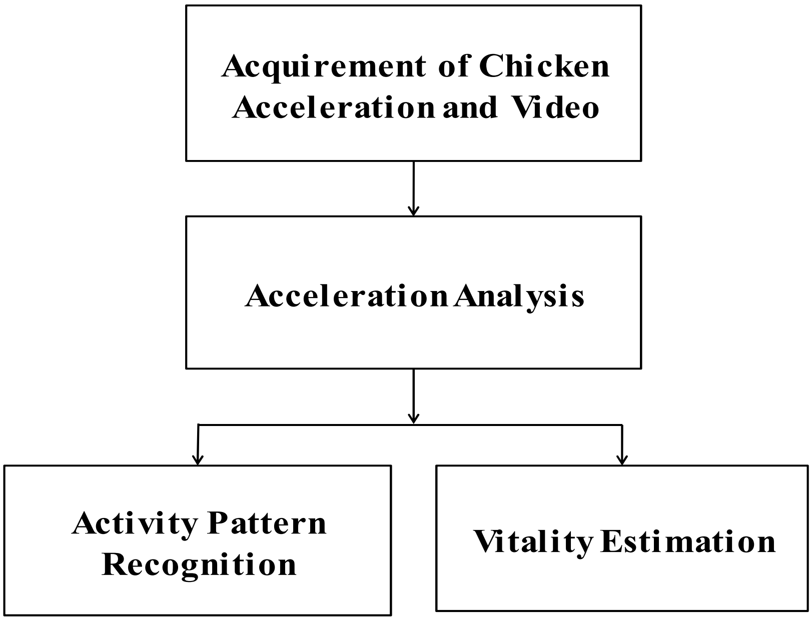

Fig. 3-1 Approach flowchart

3.2 Acceleration Signal Acquisition and Pre-processing

The acceleration signal acquisition of chickens is the first stage in the process of the activity pattern recognition and vitality estimation. To achieve this goal, a tiny acceleration logger to record the acceleration signal of chicken is designed and created. In this section, an acceleration logger device will be introduced first. And then, the environment of chicken house where to collect acceleration signal will be described. Next, the acquisition of acceleration signal will be presented. Finally, acceleration pre-processing and activity labeling will be mentioned.

3.2.1 Acceleration Logger

The acceleration logger is a device to collect acceleration data through wireless transmission. The structure diagram of acceleration logger is shown in Fig. 3-2. It contains two parts, an acceleration transmitter and a receiver. The acceleration transmitter is in charge of acceleration detection, and then transmits wirelessly the acceleration signal to the receiver connected with a computer. Finally, the received raw data are recorded in the computer.

The dimensions of the acceleration transmitter are 47 mm * 23 mm * 13 mm. Its weight is about 14 g. The max linear sensing range is ±3.6 G, and beyond this range is nonlinear. And the sampling frequency is 50 Hz. The acceleration transmitter is powered by a 3.7 V Li-ion battery. For providing steady voltage 3 V to SimpleNode and 2.5 V to ADXL330, two LDO linear voltage regulators are used to achieve this. The ADXL330 senses the acceleration in 3-axis, X, Y, Z and outputs corresponding voltage. The output pins are connected in parallel with 0.1 μF capacitors to form a low-pass filter with bandwidth 50 Hz for noise filtering. The microcontroller in SimpleNode receives the filtered signals through embedded ADC converters, and then transmits the data to the acceleration receiver via ZigBee IC. Next, the microcontroller in the acceleration receiver stores the data in the computer through UART interface with baud rate 57,600 bps.

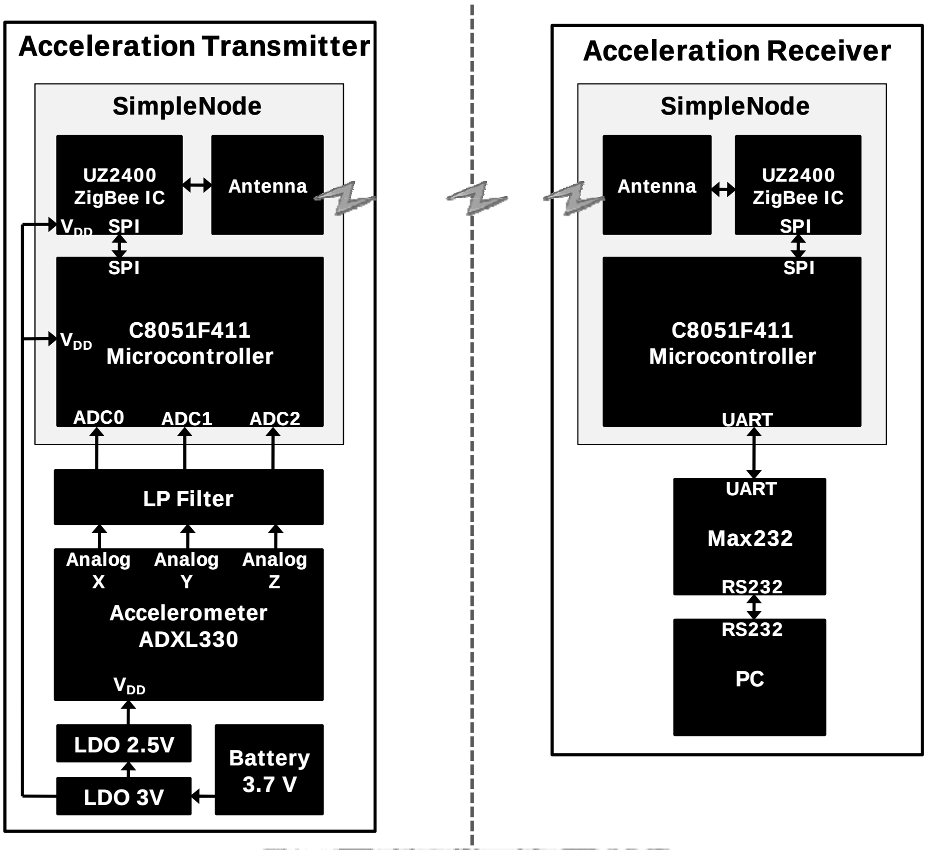

Fig. 3-2 Structure diagram of acceleration logger

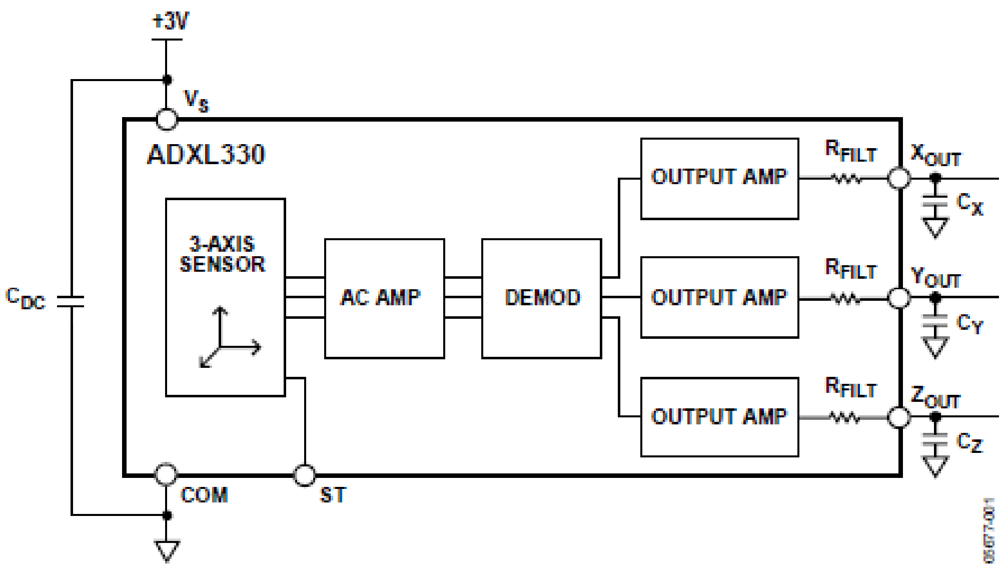

Fig. 3-3 Function Block diagram of ADXL330 (Analog Devices, 2006)

The main components of the acceleration logger include two LDO linear voltage regulators, an accelerometer, and two ZigBee devices. The accelerometer ADXL330 is a tiny, low-power, 3-axis MEMS accelerometer developed by Analog Devices, Inc. The linear sensing range of the ADXL330 is ±3.6 G, and it can sense the static acceleration of gravity (Analog Devices, 2006). This sensor has been widely used in many applications. One of the most well known is implemented in Nintendo Wii Remote controllers. The function block diagram of ADXL330 is shown in Fig. 3-3 where the operating voltage ranges from 1.8 V to 3.6 V. A capacitor for decoupling needs to be added in parallel to the power input. The ST pin is used for self-testing. The output pins in X, Y, Z are paralleled with the capacitors for anti-aliasing and noise reduction. In this study, ADXL330 module is connected in parallel with 0.1 μF output filter capacitors and 0.1 μF decoupling capacitors at power line.

Two parameters in the ADXL330 need to be measured for the calculation of the detected acceleration. One is *sensitivity*, which is used to describe output voltage V_A versus sensed acceleration A. The other is zero G bias V_{bias}, which indicates an offset, typically $V_S/2$. These two parameters are usually affected by operating voltage V_S. The formula to calculate acceleration is shown in Eq. (3-1).

SimpleNode is a WSN Device based on ZigBee, developed by Wireless Sensor Network Center (WSNC, 2007), National Taiwan University. It consists of C8051F411 microcontroller (Silicon Laboratories, 2008), UZ2400 ZeeBee IC (UBEC, 2005), and antenna. The microcontroller in SimpleNode contains a 12-bit ADC with four selectable input pins which are used to read acceleration voltages V_A from ADXL330. The conversion formula of the ADC is shown in Eq. (3-2), where reference voltage V_{REF} is 2.2 V in the study; the converted value D is raw data in this study.

$$A = \frac{(V_A - V_{bias})}{sensitivity} \quad (3\text{-}1)$$

$$V_A = V_{REF}\frac{D}{4096} \quad (3\text{-}2)$$

There are two LDO (low-dropout) regulators used in this study, TI TPS73125 2.5 V and TPS73130 3.0 V (Texas Instruments, 2009). The LDO components are widely used in Li-ion battery based products. The LDO could work under small voltage difference between input and output. In this study, TPS73125 provides 2.5 V to ADXL330, and TPS73130 supplies 3.0 V to SimpleNode. The schematic of acceleration transmitter is shown in Fig. 3-4, and the products are shown in Fig. 3-5.

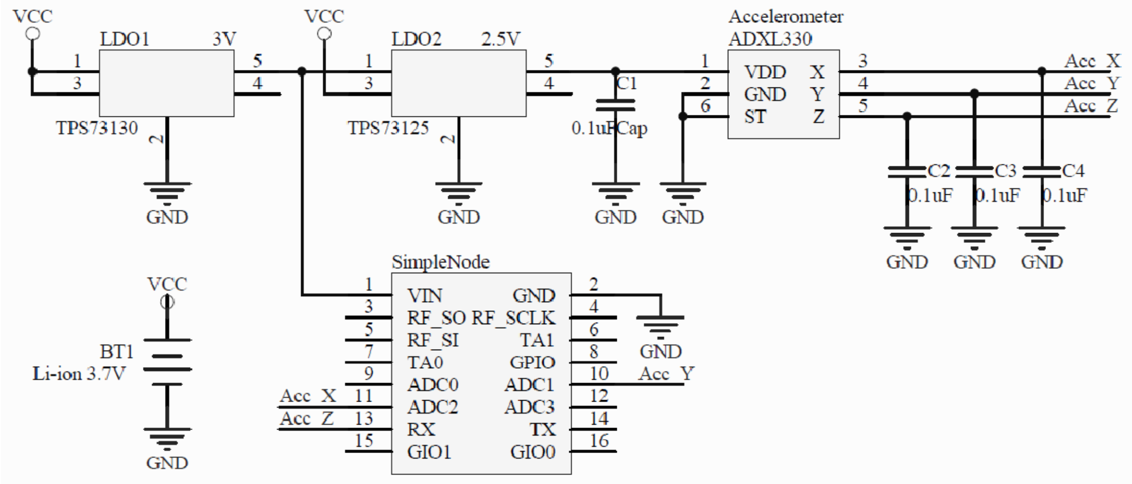

Fig. 3-4 Schematic of acceleration transmitter

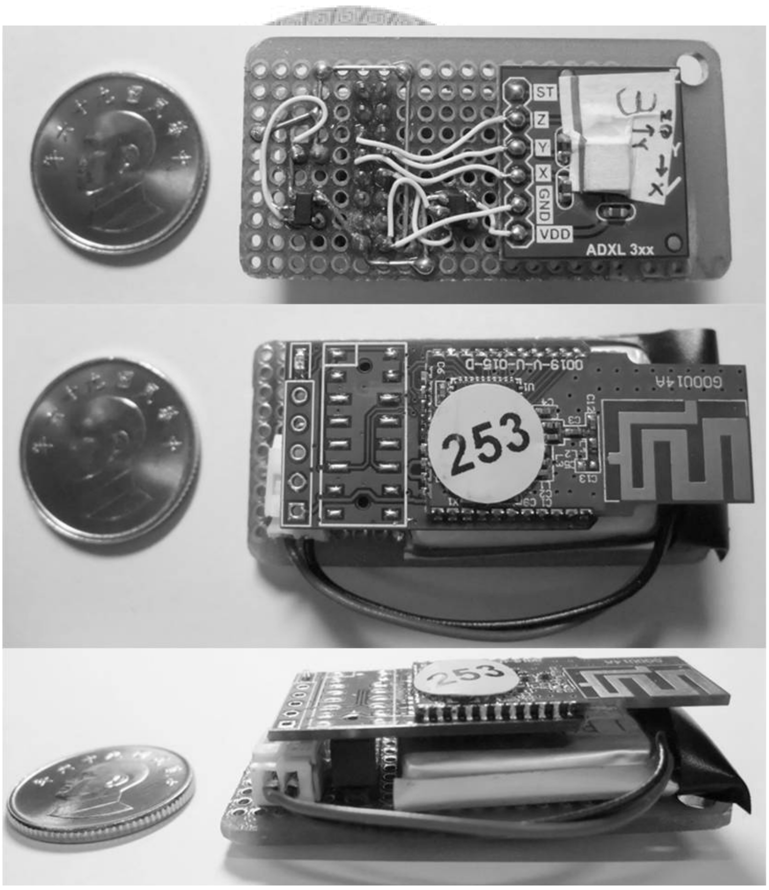

Fig. 3-5 Entities of acceleration transmitter

3.2.2 Signal Acquisition

The experimental chicken house is located in the Department of Animal Science and Technology at National Taiwan University. The house is divided into three sections as shown in Fig. 3-6 and is equipped with a cooling pad ventilation system. Each section has 4 m long and 2 m wide. The one in the middle is used for our experiment, where a laying nest, a feed trough, and a water trough are placed inside. Two cocks and thirteen hens are reared, and the corresponding stocking density is 1.875 birds/m^2. The species of reared chicken is Cobb Avian 48 broiler breeder. The chickens are born out of season. The acceleration signals are collected at the age of 82 weeks of chickens.

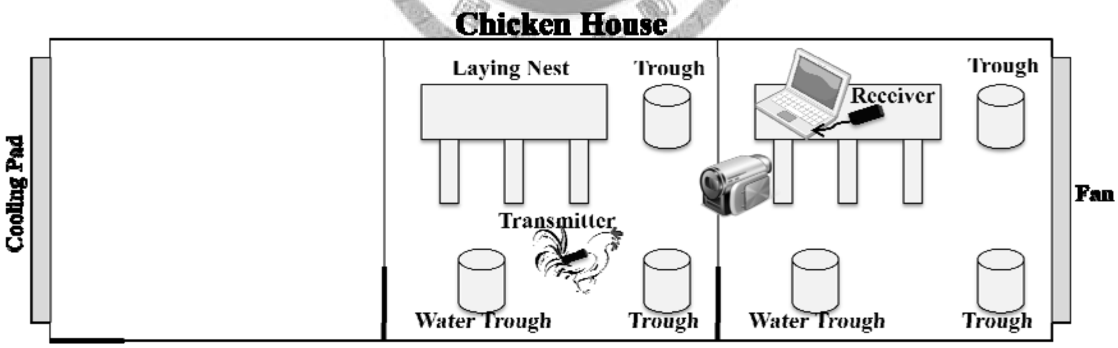

Fig. 3-6 Layout of chicken house

The environment control and feeding simply follow Cobb Avian breeder management guide published in 2008. The environment control system includes a fan, a pad, and light sources. The fan turns on while temperature is higher than 22°C and the pad turns on and off at temperature higher than 31°C and lower than 30°C, respectively. The lighting is on from 5:00 to 22:00, lasting 17 hours.

The feeding plan is that the diary feed for over 80-week chickens is 420 kcal/bird referred to Cobb Avian breeder management guide. Male and female chickens eat altogether. The brand of feed is Uni-President Enterprise Corp, and the Metabolizable Energy (ME) is 2800 Kcal/kg. The feed is measured the day before, and put it in two troughs once a day. Unlimited water is provided by water trough. Since the chickens eat altogether, the weight of chicken is difficult to control. Nevertheless, the weight of chicken is not our major concern in this study.

The acceleration receiver, computer, and DV recorder are put in the section next to the middle section. The acceleration transmitter is attached on the back of a cock to collect acceleration signals. In the mean time, the DV records chicken's activity simultaneously.

In this study, RealTerm is a software for serial communication used to transmitting receiving and recording serial data. The recorded data includes recording time, acceleration logger ID, wireless package sequence, and raw data in X-axis, Y-axis, and Z-axis. The recorded data format is shown in Fig. 3-7.

Recorded Time	Logger ID	Package Sequence	X-axis Raw Data	Y-axis Raw Data	Z-axis Raw Data
40428.5068163	1	124	2280	2078	1828
40428.5068168	1	125	2264	2079	1834
40428.5068169	1	126	2256	2080	1825
40428.5068172	1	127	2258	2082	1832

Fig. 3-7 Format of recorded data

3.2.3 Signal Pre-processing

A couple of procedures should be done before conducting the activity pattern recognition and vitality estimation. The first one is to process acceleration raw data. The second one is to convert raw data into corresponding acceleration signal. The third one is to match the acceleration signal with specific activity shown in the video clip.

It is likely to lose packages during wireless data transmission and to cause data errors due to asynchronous serial communication. Two measures are taken to restore the raw data by removing error data and adding missing data by interpolation based on smoothing the sequence.

The raw data are transformed into acceleration by using Eq. (3-3) which is modified from Eq. (3-1) and Eq. (3-2).

$$A = (V_{REF}\frac{D}{4096} - V_{bias})/sensitivity \tag{3-3}$$

After the raw data is converted into acceleration, the acceleration data and content in the video clips will be compared and matched. Hence, the specific activity will be labeled on the acceleration signal. The labeling includes the start time, end time, and pattern of activity. Five activity patterns in this study are covered, i.e., R for Rest or motionless, W for walking, P for pecking, eating or drinking, U for sit-down and stand-up, and O for other activities hard to be recognized.

3.3 Activity Pattern Recognition

In this section, the framework of activity pattern recognition will be first introduced. Then the construction and validation of the recognition model will be illustrated.

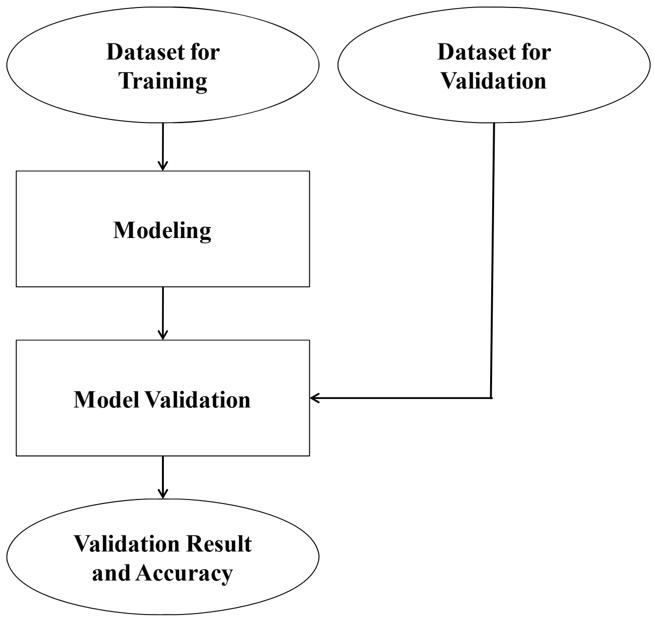

Fig. 3-8 Flowchart of pattern recognition

Fig. 3-8 shows the flowchart of the activity pattern recognition algorithm. Datasets should be prepared and processed before constructing models and performing activity pattern recognition. They are categorized into training, validation, and testing datasets. Training and validation datasets are used to construct and validate recognition models, respectively. And the testing datasets are employed to test models. The model with highest accuracy is selected to predict the pattern of unknown datasets.

3.3.1 Dataset Preparation

In this study, four datasets need to be prepared for activity pattern recognition, which are homogeneous datasets for training, validation, testing, and heterogeneous dataset for testing. The procedures of dataset preparation are shown in Fig. 3-9.

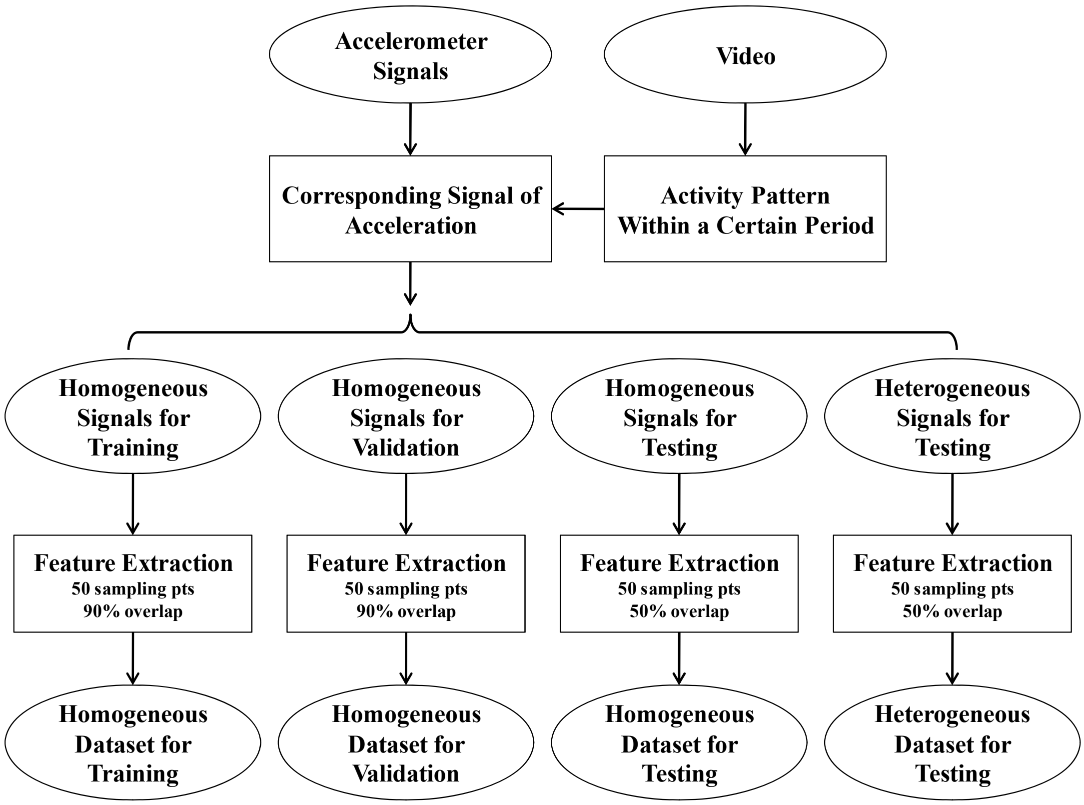

Fig. 3-9 Dataset Preparation for activity recognition

3.3.1.1 Homogeneous Signals

The collected acceleration signals are aligned and matched with their corresponding activity patterns shown in video installed in the chicken house. Based on the each individual activity synchronized with the video, the acceleration signals are further clipped into homogeneous signals for training, validation and testing.

A sliding window is designed to clip signals with fixed length of samples and certain percentage overlapping with its neighboring windows. Features are extracted and calculated from signal in one sliding window. In the study, the window for the homogeneous signal of training and validation is set at size of 50 samples which last one second, and then shifts 5 samples, i.e., 90% overlapping, to the next.

In practical application, feature calculation will be time consuming if sliding windows with 90% overlapping. Therefore, 50% overlapping, 25 samples shift for the window size of 50 samples, is applied to the homogeneous signal for testing, and the heterogeneous signal for testing in consideration of both efficiency and prediction accuracy.

A specific segment of homogeneous signal is the collection of signals only corresponding to one single activity pattern as shown in Fig. 3-10.

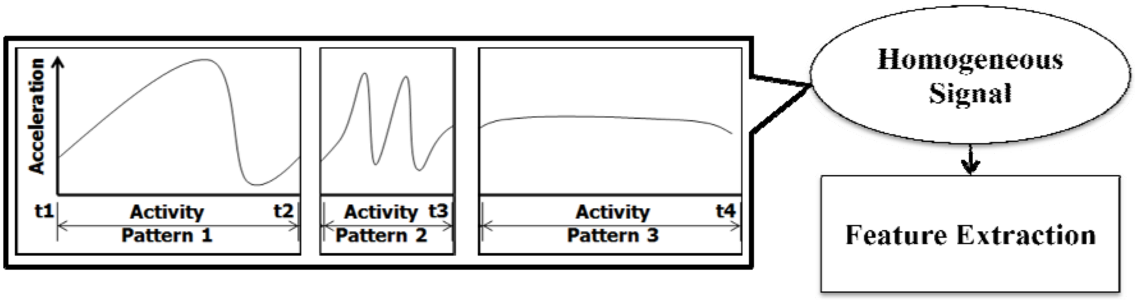

Fig. 3-10 Homogeneous signal

3.3.1.2 Heterogeneous Signals

In fact, the activity pattern of acceleration signal is unknown in practical application. Therefore the signal cannot be divided according to its activity pattern beforehand. The clipped signals by sliding window may contain more than one activity patterns as shown in Fig. 3-11. Therefore, test with heterogeneous signals, which may have lower recognition accuracy, is proposed to evaluate the models.

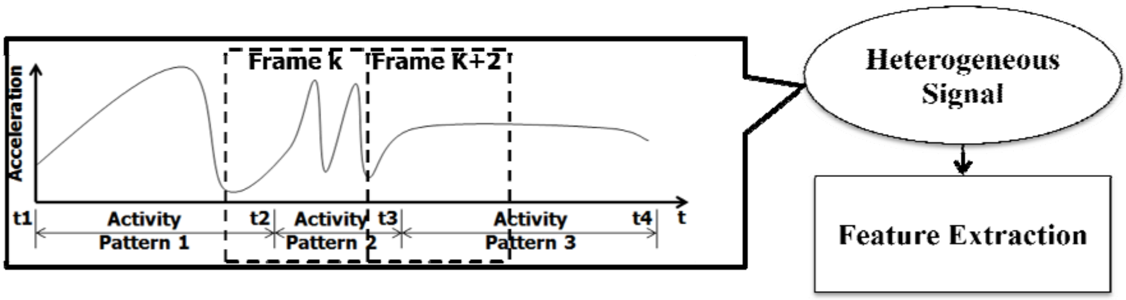

Fig. 3-11 Heterogeneous signal

3.3.1.3 Feature Extraction

The homogeneous or heterogeneous datasets are the feature sets extracted from the corresponding homogeneous or heterogeneous signal, individually.

The features of various activity patterns may be distinguishable on specific frequency bands of acceleration signals and on the other bands may not be true. Therefore, features calculated from various frequency bands might be necessary. For features extracted from the signal of different frequency bands, the signal needs to be decomposed into the signals in different frequency bands in advance. Wavelet transform is one of the best choices to achieve this purpose.

3.3.1.3.1 Wavelet Transform

Fourier transform is a traditional method to analyze signals in frequency domain, but it does not contain information of time domain. Short-time Fourier transform uses short-time window to partially solve this problem. However, the fixed window size is less flexible in accurately identifying time point or duration. In general, low frequency signal lasts longer, so a window with larger size may be enough; however, signals with high frequency changes rapidly, which require short-time window to quantify their properties.

The wavelet transform could automatically adjust window size according to signal frequency. A wavelet basis could generate bases with different resolution in time and frequency domain through dilation and translation. There are many different wavelet bases, e.g., Harr, Coiflet, Mexicana hat, Morlet, Daubechies, etc. The basis of Daubechies 11 (Daubechies, 1988) which is indicated by db10 in MATLAB as shown in Fig. 3-12 (a) is applied in the study. Bases with different resolution could form a set of wavelet package bases shown in Fig. 3-12 (b).

To be done in a computer, wavelet transform needs to be discretized. The discrete filter bank algorithm is performed with the structure shown in Fig. 3-12 (c), A signal x[n] is divided into high frequency component D_1 and low frequency component A_1 through level 1 wavelet transform, where HP block represents a high-pass filter; LP block means a low-pass filter; ↓2 block is a down-sampling process. The algorithm is constructed by a series of high-pass, low-pass filter and downsampling procedures. A_1 component can be further decomposed into high frequency component D_2 and low frequency component A_2 through level 2 wavelet transform. Processes for the analysis of the following levels are similar. The frequency property for each component is shown in Fig. 3-12 (d), and the f_n is an Nyquist frequency of the input signal x[n].

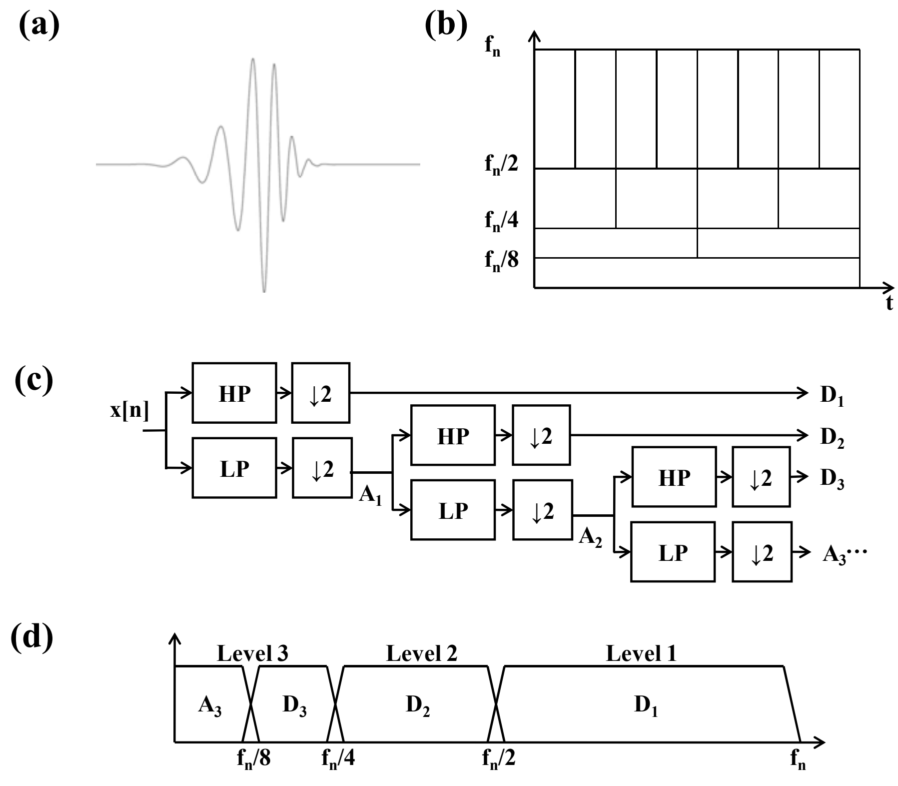

Fig. 3-12 Wavelet Transform (a) DB10 basis (b) Time-frequency boxes of wavelet package basis (c) Discrete filter bank algorithm (d) Filter bank

In this study, 5-level decomposition is performed to obtain the signals of different frequency bands which are D_1, D_2, D_3, D_4, D_5 and A_5, and then these signals will be used to calculate features of specific frequency bands.

3.3.1.3.2 Feature Selection

Before feature extraction is performed, what kinds of features are essential for activity recognition should be evaluated. Careful feature selection for the model may enhance the power of classification. Hence, a feature selection process will be executed first. The features of signals in literatures consist of mean (Lester *et al.*, 2006; Huynh and Schiele, 2005; Ermes *et al.*, 2008; Pirttikangas *et al.*, 2006; Wang *et al.*, 2005; Yang, 2009; Yang *et al.*, 2008), variance (Lester *et al.*, 2006; Pärkkä *et al.*, 2006; Huynh and Schiele, 2005; Ermes *et al.*, 2008; Yang *et al.*, 2008), standard deviation (Pirttikangas *et al.*, 2006; Wang *et al.*, 2005; Yang, 2009; Yang *et al.*, 2008), correlation among data in various axes (Lester *et al.*, 2006; Huynh and Schiele, 2005; Pirttikangas *et al.*, 2006; Wang *et al.*, 2005; Yang, 2009; Yang *et al.*, 2008), median (Pärkkä *et al.*, 2006; Ermes *et al.*, 2008), 25th percentile (Ermes *et al.*, 2008), 75th percentile (Ermes *et al.*, 2008; Yang, 2009), interquartile range (Yang, 2009; Yang *et al.*, 2008), root mean square (Yang *et al.*, 2008), peak numbers (Ward *et al.*, 2006), principal frequency (Pärkkä *et al.*, 2006), power of principal frequency (Pärkkä *et al.*, 2006; Ermes *et al.*, 2008), spectrum energy (Wang *et al.*, 2005; Huynh and Schiele, 2005; Yang *et al.*, 2008), spectrum entropy (Huynh and Schiele, 2005; Ermes *et al.*, 2008; Wang *et al.*, 2005; Yang, 2009), power of principal frequency of different frequency bands (Ermes *et al.*, 2008), etc. Besides, principal frequency of different frequency bands and energy of different frequency bands are also used in this study. The features in different frequency bands realized by wavelet transform are also investigated in this study.

Among 96 features for three-axis, 27 features are selected for feature extraction based on box-and-whisker plots of features, which can distinguish an activity pattern from others. Two examples are used to illustrate the ideas. The correlation coefficient of signals in X-axis and Y-axis shown in Fig. 3-13 could tell at least 50% of activity pattern "W" from other activity patterns. And interquartile range of Y-axis in Fig. 3-14 could also differentiate most of activity pattern "R" and "O" from other activity pattern. Other undistinguished activity pattern could be distinguished via other useful features as well. Hopefully, all activity patterns could be all distinguished.

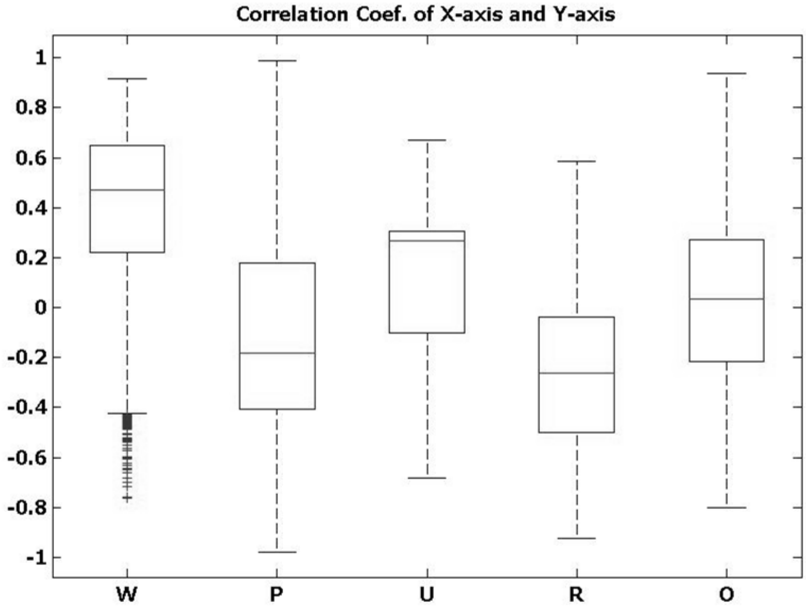

Fig. 3-13 Box-and-whisker plot for correlation coefficient of signals in X-axis and Y-axis

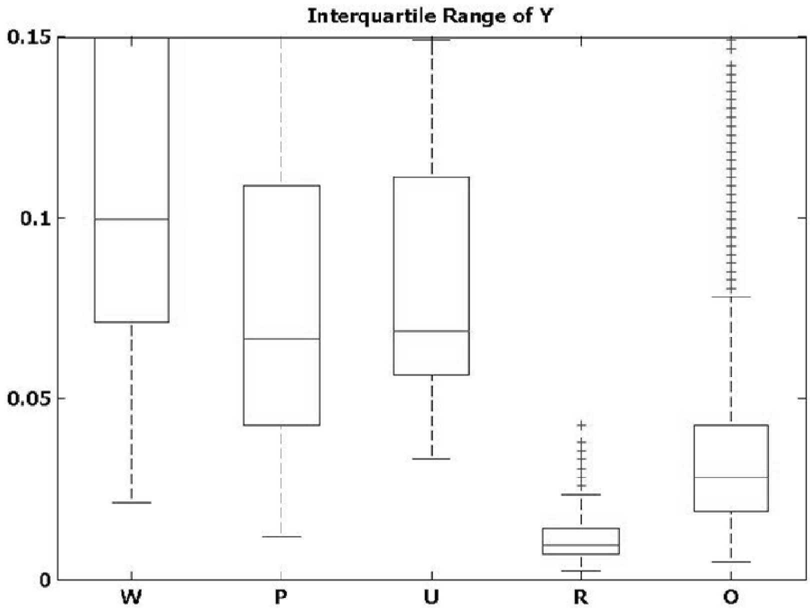

Fig. 3-14 Box-and-whisker plot for interquartile range of Y-axis

In this study, the 27 selected features are correlation coefficient in X-axis and Y-axis, interquartile range of X, peak number of X, spectrum energy of X, spectrum entropy of X, D1 power of peak frequency of X, D1 energy of X, D3 power of peak frequency of X, D3 energy of X, D4 peak frequency of X, A5 peak frequency of X, median of Y, interquartile range of Y, peak number of Y, D1 power of peak frequency of Y, D1 energy of Y, D3 energy of Y, D4 peak frequency of Y, D5 peak frequency of Y, median of Z, interquartile range of Z, peak number of Z, power of peak frequency of Z, D1 power of peak frequency of Z, D3 power of peak frequency of Z, D3 energy of Z, D5 peak frequency of Z.

3.3.1.4 Homogeneous and Heterogeneous Datasets

The homogeneous and heterogeneous datasets are prepared once the feature extraction is done. Each homogeneous dataset has its unique pattern. However, the activity pattern in heterogeneous dataset may contain more than one activity patterns and needs to be classified to the activity pattern with the highest percentage. That is that the winner pattern compared with other patterns occupies highest percentage of duration in the clip. However, an exception is that a clip of signal contains activity pattern rest “R” and other activity patterns. To be classified as “R” is not based on majority. The percentage of rest has to be over a specific threshold, which is set at 92% in the study. Otherwise, it is referred to as the other activity patterns.

3.3.2 Model Selection

In model selection process, two-step process is performed. The first step is candidate model selection. The second step is candidate model testing. In the end, a winner model will be chosen based on the best performance of activity pattern recognition.

3.3.2.1 Candidate Model Selection

The section is to illustrate how the candidate models are selected from 63 models. 10-fold cross-validation is used to build and validate models with homogeneous dataset as shown in Fig. 3-15. The 10-fold cross-validation divides dataset into 10 parts; 9 parts out of the 10 are chosen as training set to build model and the rest for validation till each part has served as a validation set in turn. Finally, the preliminary candidate models are chosen for averaged accuracy higher than 85%.

Weka software version 3.6.4 is used to build and validate models in this study. Weka, developed by Machine Learning Group at University of Waikato, is a freeware which is the collection of more than 110 machine learning algorithms for data mining (Weka, 2010).

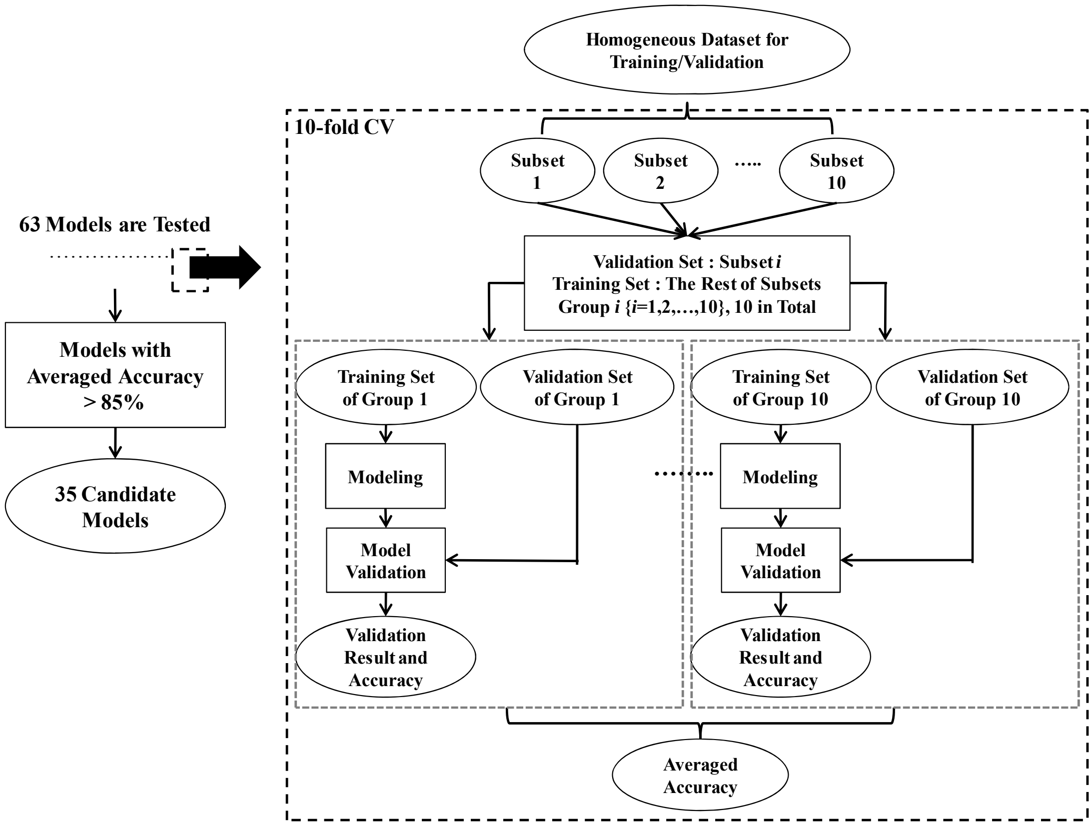

Fig. 3-15 Model selection with training/validation data

3.3.2.2 Model Testing

In model testing phase, these selected candidate models will then be tested with both homogeneous and heterogeneous datasets, respectively. Signals are collected on another day for those datasets to estimate the prediction ability of model. Finally, the best model is chosen based on the accuracy of prediction in the test shown in Fig. 3-16.

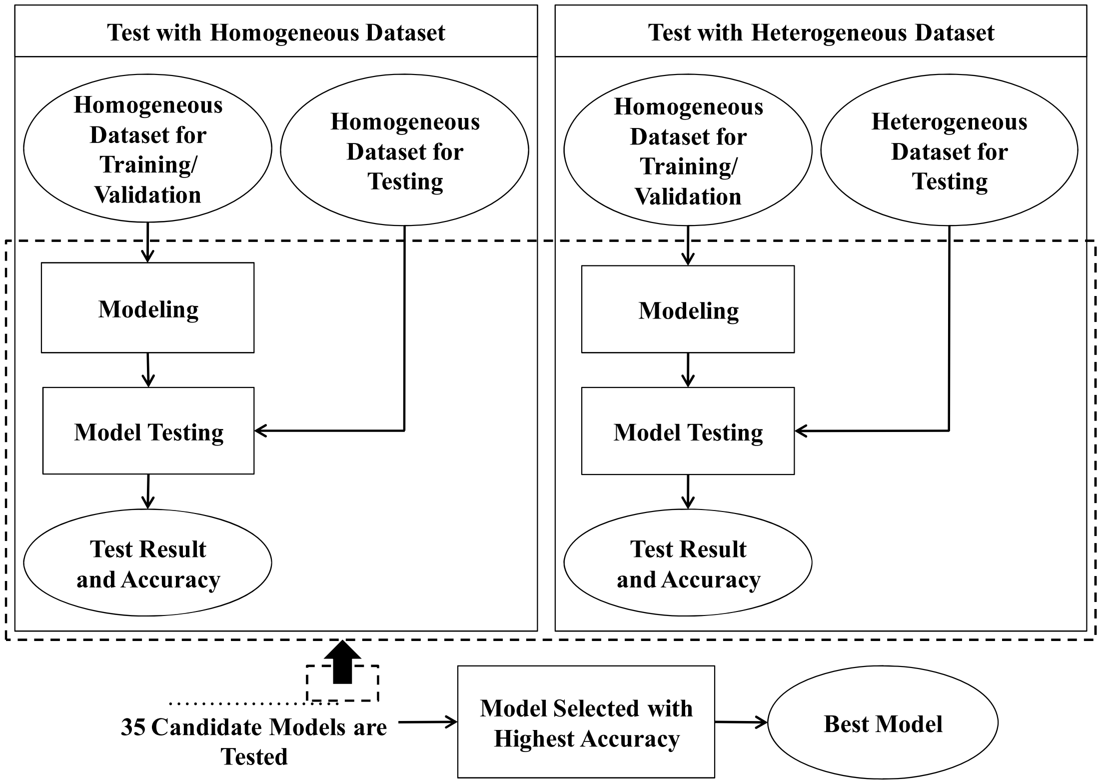

Fig. 3-16 Model selection with testing data

3.4 Vitality Estimation

The vitality could be estimated by various ways. In general, the chicken with higher vitality walks around or moves about more often. In the study, the average power of acceleration signals is used as the index of vitality. Average power is energy divided by the number of sampling points. Start time, end time, and duration of motion need to be first estimated to obtain the index value, which forms the frame of acceleration signal representing activity, defined as an activity frame. Subsequently, the average power of the signal can be calculated.

3.4.1 Determination of Activity Frame

The acceleration signals contains gravity component on 3-axis and noise, which should be filtered out before the detection of activity frame. In this study, wavelet transform with Daubechies 11 basis is used to decompose 3-axis acceleration signals into signals in different frequency bands as shown in Fig. 3-17. To filter out gravity component on 3-axis, low-frequency signal components A5 are discarded. For noise reduction, D1 is excluded, which is the component of the highest frequency. Finally, the signals of D2, D3, D4, and D5 are synthesized to form signals in X, Y, and Z, which have expelled the gravity component and noise as shown in Fig. 3-18.

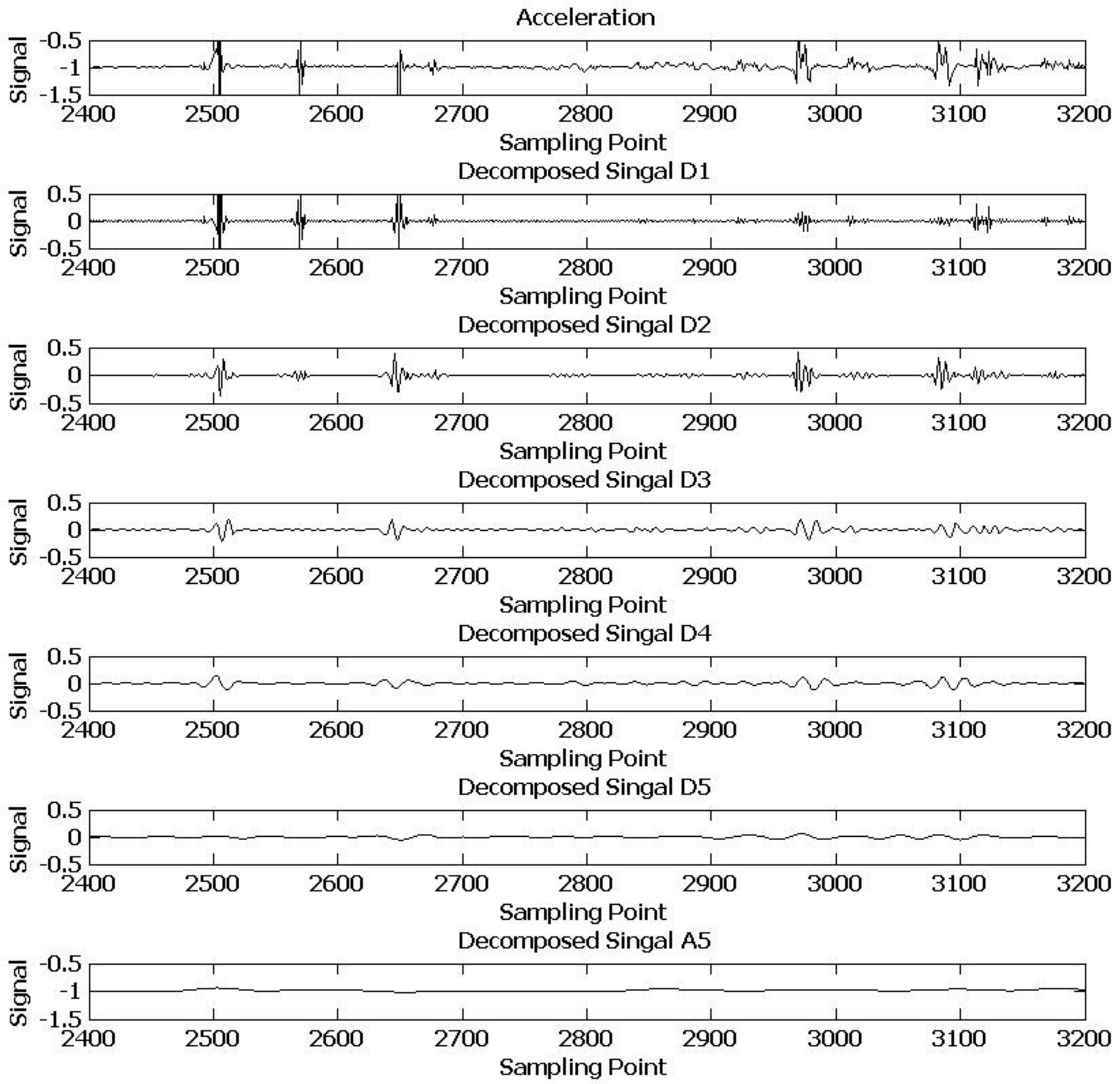

Fig. 3-17 Signal decomposed by wavelet basis db10

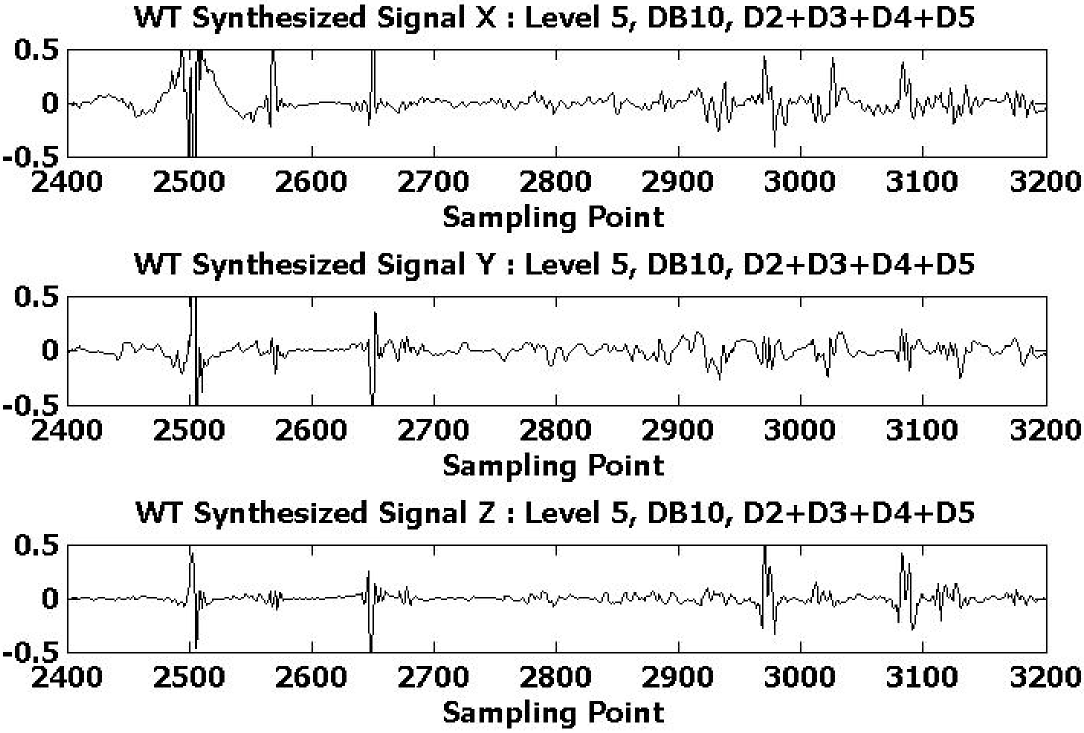

Fig. 3-18 Synthesized signals in 3-axis

Next, the activity frames are decided from the synthesized signals by thresholding. However, the synthesized signal may contain weak signals which could be excluded. In this study, averaged power calculation with l sample points is taken to reduce the effect of those weak signals and not to ignore meaningful signals.

There are three steps in activity frame determination. The first one is to calculate the averaged power of the synthesized signals in every l = 5 sampling points in our study. The averaged power formula in X, Y, and Z are shown in Eq. (3-4), Eq. (3-5), and Eq. (3-6). The P_X, P_Y, P_Z and A_{syn_X}, A_{syn_Y}, and A_{syn_Z} are the averaged power and the synthesized signals, respectively. l in these equations, 5 time points in this study, indicates the duration where power is accumulated.

$$P_X[j] = \frac{1}{l} \sum_{k=(j-1)*l+1}^{(j-1)*l+l} \left| A_{syn\_X}[k] \right|^2 \tag{3-4}$$

$$P_Y[j] = \frac{1}{l} \sum_{k=(j-1)*l+1}^{(j-1)*l+l} \left| A_{syn\_Y}[k] \right|^2 \tag{3-5}$$

$$P_Z[j] = \frac{1}{l} \sum_{k=(j-1)*l+1}^{(j-1)*l+l} \left| A_{syn\_Z}[k] \right|^2 \tag{3-6}$$

The second one is to decide the activity frames from the average power over a specified threshold. The thresholds in 3-axis may not be the same. Fig. 3-19 shows the preliminary activity frames. The last step is combining these activity frames in considering of frames in 3-axis by union, neighboring joining and spike deletion shown in Fig. 3-20.

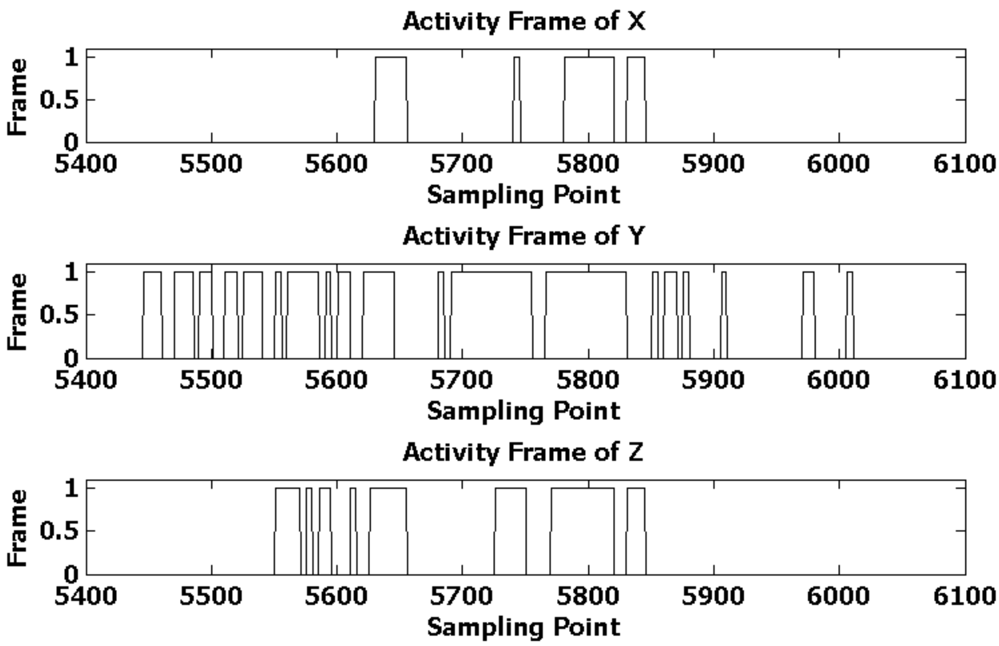

Fig. 3-19 Activity frames of X-axis, Y-axis, and Z-axis

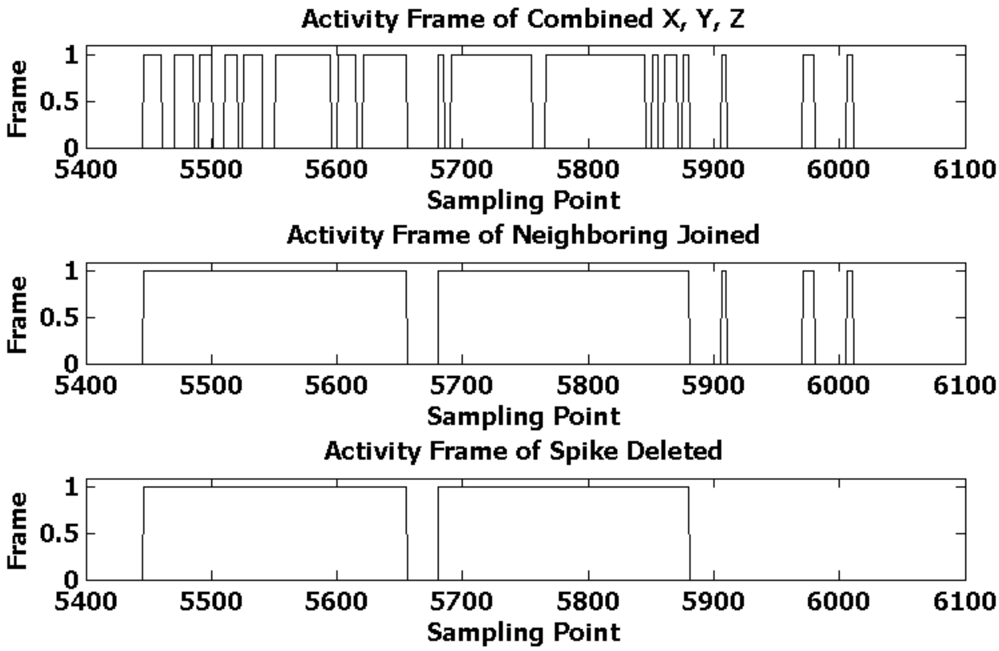

Fig. 3-20 Activity frame post-processing

3.4.2 Estimation of Average Power for Activity Frame

The vitality index in this study is the average power $P[i]$ for a specific activity frame, shown in Eq. (3-7). The average power is calculated by Eq. (3-7) to Eq. (3-11). The A_{syn_X}, A_{syn_Y}, and A_{syn_Z} are the synthesized signals in 3-axis. i indicates the number of activity frame. The $s[i]$ is the start point of activity frame i. The $l[i]$ is the length of activity frame i. The $E_{Frame\_X}[i]$, $E_{Frame\_Y}[i]$, $E_{Frame\_Z}[i]$ are the energy of activity frame i in 3-axis. Finally, the average power of all activity frames can be obtained to represent the vitality of chicken.

$$P[i] = E[i]/l[i] \tag{3-7}$$

$$E[i] = E_{Frame\_X}[i] + E_{Frame\_Y}[i] + E_{Frame\_Z}[i] \tag{3-8}$$

$$E_{Frame\_X}[i] = \sum_{k=s[i]}^{s[i]-1+l[i]} \left|A_{syn\_X}[k]\right|^2 \tag{3-9}$$

$$E_{Frame\_Y}[i] = \sum_{k=s[i]}^{s[i]-1+l[i]} \left|A_{syn\_Y}[k]\right|^2 \tag{3-10}$$

$$E_{Frame\_Z}[i] = \sum_{k=s[i]}^{s[i]-1+l[i]} \left|A_{syn\_Z}[k]\right|^2 \tag{3-11}$$

Chapter 4 Results and Discussion

The results of this study will be shown and discussed in the following sections. In section 4.1, the results of candidate models selection via 10-fold cross-validation will be illustrated. Next, the results of the candidate model testing with homogeneous dataset and heterogeneous dataset will be demonstrated. Finally, Bayesian network classifier is the winning model and the recognition detail on Bayesian network classifier is illustrated. The results of the vitality estimation are presented in section 4.2. Comprehensive discussion on the results and relevant problems will be given and addressed in section 4.3.

4.1 Activity Recognition

A signal for training and validation with 1930 seconds in total is shown in Fig. 4-1, and a signal for testing with 122 seconds long which are collected on another day is shown in Fig. 4-2. They are prepared for activity pattern recognition.

Subsection 4.1.1 presents the result of the candidate model selection via 10-fold cross-validation with the homogeneous dataset for training and validation. The testing result of the candidate models with homogeneous and heterogeneous datasets is presented in subsection 4.1.2. In subsection 4.1.3, the validation and testing for

Bayesian network classifier will be mentioned in details.

The ground in chicken house paved with rice hulls or soil is uneven. The uneven ground and the stoop of chicken will cause the tilting of accelerometers attached on the back of chicken, thus affect the components of gravity projected on three axes. In the study, X-axis is aligned with the lateral direction of chicken, and the longitudinal direction of chicken is coincided with Y-axis. The recognition accuracy can be improved if the interference mentioned above can be carefully dealt with.

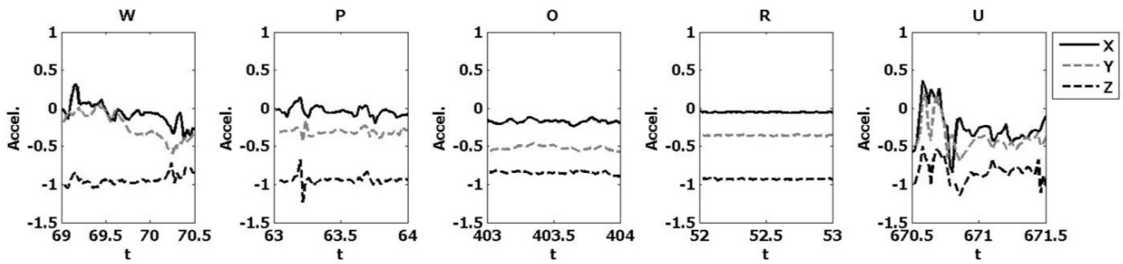

Fig. 4-1 Acceleration signal for training and validation

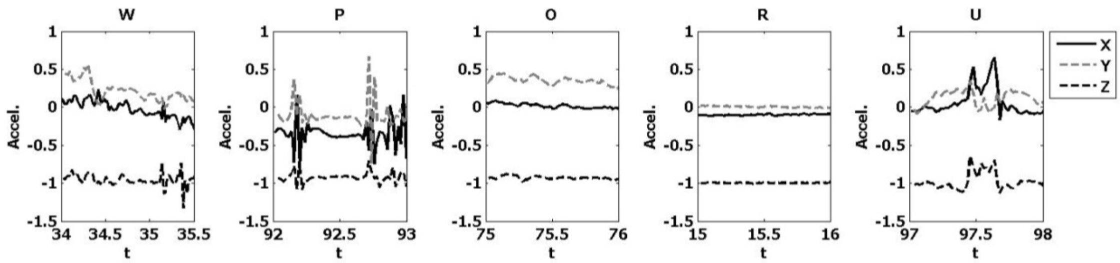

Fig. 4-2 Acceleration signal for testing

4.1.1 Candidate Model Selection via 10-fold Cross-Validation

The models with accuracy higher than 85% through 10-fold cross-validation will be chosen as candidate models for further model testing. There are 35 candidate models in total. The models and their corresponding accuracies are shown in Table 4-1. The abbreviated names of models just follow the definition in Weka software, e.g., BayesNet represents Bayesian network classifier.

4.1.2 Model Tested with Homogeneous and Heterogeneous Datasets

Table 4-2 shows the result of model testing with homogeneous and heterogeneous datasets. Though the accuracy of Bayesian network classifier in 10-fold cross-validation does not rank on top, 86.10% accuracy is still satisfied and gets into the final list. The accuracy in model testing with homogeneous dataset is 74.42%, and testing with heterogeneous dataset is also up to 72.10%. The Bayesian network classifier outperforms on both two datasets. Therefore, the Bayesian network classifier is more suitable to be the classification model than the others are in this study.

Table 4-1 Accuracy of candidate models on 10-fold cross-validation

Model	Accuracy (%)	Model	Accuracy (%)
RandomCommittee	95.12	AttributeSelectedClassifier	90.15
RandomForest	94.46	FT	89.90
RotationForest	94.43	LogitBoost	89.73
END	94.22	SimpleCart	89.65
Decorate	94.06	BFTree	89.48
ClassificationViaRegression	92.75	OrdinalClassClassifier	89.47
Bagging	92.33	Ridor	89.44
NBTree	92.33	REPTree	89.26
RandomSubSpace	92.24	DTNB	88.45
J48graft	91.46	RandomTree	88.45
KStar	91.28	RacedIncrementalLogitBoost	87.75
ND	91.24	FilteredClassifier	87.53
LMT	91.22	MultiClassClassifier	86.64
PART	91.17	SimpleLogistic	86.47
DataNearBalancedND	90.91	Logistic	86.23
J48	90.91	BayesNet	86.10
JRip	90.88	MultilayerPerceptron	85.32
ClassBalancedND	90.77		

Table 4-2 Accuracy of candidate models on validation and testing

Model	CV Accuracy (%)	Homogeneous Dataset Accuracy (%)	Heterogeneous Dataset Accuracy (%)
RandomCommittee	95.12	68.60	68.24
RandomForest	94.46	67.44	68.24
RotationForest	94.43	63.95	62.66
END	94.22	63.37	62.66
Decorate	94.06	63.95	65.24
ClassificationViaRegression	92.75	65.12	66.09
Bagging	92.33	65.12	66.52
NBTree	92.33	65.12	66.09
RandomSubSpace	92.24	70.35	69.53
J48graft	91.46	65.12	63.52
KStar	91.28	51.16	48.93
ND	91.24	60.47	62.23
LMT	91.22	57.56	60.09
PART	91.17	55.23	57.08
DataNearBalancedND	90.91	59.30	63.52
J48	90.91	64.53	61.80
JRip	90.88	65.70	64.38
ClassBalancedND	90.77	59.30	63.52
AttributeSelectedClassifier	90.15	62.79	61.80
FT	89.90	71.51	63.95
LogitBoost	89.73	69.19	66.95
SimpleCart	89.65	65.70	66.09
BFTree	89.48	66.86	64.38
OrdinalClassClassifier	89.47	54.07	57.51
Ridor	89.44	60.47	63.09
REPTree	89.26	68.02	67.38
DTNB	88.45	63.95	65.67
RandomTree	88.45	69.19	66.09

Table 4-2 Accuracy of candidate models on validation and testing (Continued)

Model	CV Accuracy (%)	Homogeneous Dataset Accuracy (%)	Heterogeneous Dataset Accuracy (%)
RacedIncrementalLogitBoost	87.75	65.70	63.95
FilteredClassifier	87.53	63.95	63.95
MultiClassClassifier	86.64	65.12	65.24
SimpleLogistic	86.47	69.77	70.39
Logistic	86.23	68.02	70.39
BayesNet	86.10	74.42	72.10
MultilayerPerceptron	85.32	51.74	54.08

4.1.3 Confusion Matrix of Bayesian Network Classifier

In the 10-fold cross-validation, 7577 instances are used. Among them, the correctly classified is 6524 instances and the incorrectly classified is 1053 instances, i.e., 86.10% accuracy. Table 4-3 shows the confusion matrix of validation, the sign “R” stands for rest or motionless, “O” for other movement hard to categorize, “W” for walk, “P” for peck body, peck stuff, eat, and drink, “U” for sit-down or stand-up.

Table 4-3 Confusion matrix of 10-fold cross-validation of Bayesian network classifier

In\Out	R	O	W	P	U
R	789	94	0	0	0
O	168	1776	140	61	11
W	0	88	1331	23	23
P	0	274	153	2616	4
U	0	3	8	3	12

From the homogeneous dataset, 172 instances are employed for model testing where the correctly classified is 128 instances and the incorrectly classified is 44 instances. The accuracy is 74.42%. Table 4-4 shows the confusion matrix of test.

In heterogeneous dataset, 233 instances are used to test the model. The correctly classified is 168 instances and the incorrectly classified are 65 instances. The accuracy is 72.10%. Table 4-5 shows the confusion matrix of test.

Table 4-4 Confusion matrix of the test with homogeneous dataset of Bayesian network classifier

In\Out	**R**	**O**	**W**	**P**	**U**
R	28	2	0	0	0
O	1	55	11	1	0
W	0	4	42	8	1
P	0	8	0	3	0
U	0	0	8	0	0

Table 4-5 Confusion matrix of the test with heterogeneous dataset of Bayesian network classifier

In\Out	**R**	**O**	**W**	**P**	**U**
R	26	1	0	0	0
O	5	80	18	9	0
W	0	4	53	8	1
P	0	8	0	9	0
U	1	1	9	0	0

The confusion matrices in Table 4-3, Table 4-4, Table 4-5 show that the samples of activity pattern “U” is much less than ones of the other activity patterns’, which is the case of model building with scarce samples. In this case, the activity pattern “U” may be easily classified as other activity patterns. A couple of methods could be applied to overcome the case with scarce samples, like weighed support vector machine, knowledge-based artificial neural networks (KBANNs), or saturation labeling for 2D-DIGE analysis, etc.

4.2 Vitality Estimation

The objective of vitality estimation is to provide management staffs on the condition of chicken activity. The test signal is shown in Fig. 4-3. The procedure to determine activity frames from acceleration signal is shown in Fig. 4-4.

After the activity frames are captured, the average power of activity frames are calculated and referred as the vitality index. Average power, which is energy divided by frame length, is a proper index to compare with the other frames for vitality evaluation. Table 4-6 shows the result of the vitality estimation. The vitality information in the table contains the number of activity frames, energy, frame length, and average power.

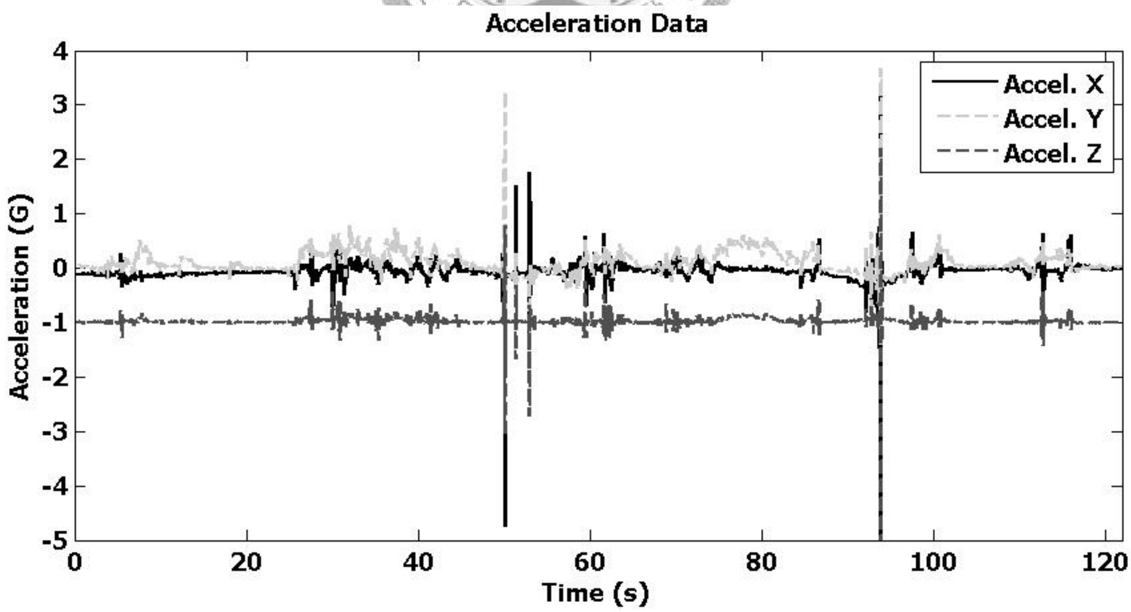

Fig. 4-3 Test signal for vitality estimation

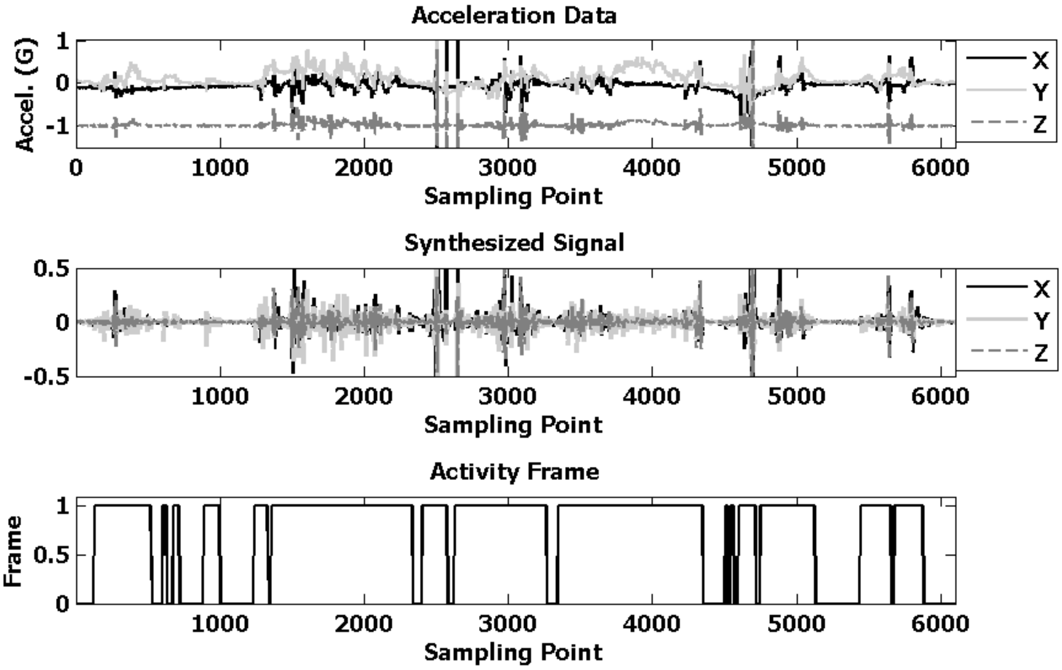

Fig. 4-4 Procedure of activity frame determination

Table 4-6 Results of vitality estimation

Frame Number	Energy (joule)	Frame Length (point)	Average Power (watts)
1	2.20	394	0.005566
2	0.21	24	0.008918
3	0.08	44	0.001842
4	0.29	109	0.002630
5	1.39	94	0.014751
6	14.94	974	0.015335
7	35.27	174	0.202686
8	12.21	634	0.019257
9	7.81	1004	0.007779
10	0.03	14	0.002151
11	0.03	19	0.001563
12	41.38	114	0.363007
13	3.67	379	0.009675
14	2.23	209	0.010660
15	2.92	199	0.014665

Chapter 5 Conclusions

In this study, a system to recognize activity pattern and estimate vitality of chicken based on signals from a 3-axis accelerometer is developed, where the activity recognition algorithm employs Bayesian network classifier to predict activity patterns and the average power based vitality estimation algorithm can be obtained by wavelet transform, activity frame determination, and energy calculation. The developed algorithm can achieve the performance up to 86.10% accuracy by 10-fold cross-validation with homogeneous dataset for both training and validation, 74.42% and 72.10% in model testing on homogeneous dataset, and heterogeneous dataset respectively.

The recognition and estimation is now conducted off-line. To accomplish the objective of pre-warning of chicken in sick, an on-line system needs be further developed. The separated algorithms on activity recognition and vitality estimation could be also further integrated together in the future work.

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