Design and Implementation of Intelligent Fitness Management (IFM) System based on Personalized Exercise Guidance for Obesity

Yeon Sik Noh

The Graduate School
Yonsei University
Department of Biomedical Engineering

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Yeon Sik Noh

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This certifies that the dissertation of Yeon Sik Noh is approved.

Thesis Supervisor: Prof. Hyungro Yoon

Prof. Wonky Kim: Thesis Committee Member #1

Prof. Youngho Kim: Thesis Committee Member #2

Prof. Gye Rae Tack: Thesis Committee Member #3

Dr. In Deok Kong: Thesis Committee Member #4

The Graduate School

Yonsei University

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Abbreviations

ACSM	American College of Sports Medicine
ANS	Autonomic Nervous System
ECG	Electrocardiogram
EMG	Electromyogram
FFT	Fast Fourier Transform
FOPDT	First Order Plus Dead Time
GUI	Graphic User Interface
HDL	High-Density Lipoprotein
HR	Heart Rate
HRmax	Maximum of Heart Rate
HRrest	Resting Heart Rate
$\mathbf{K_P}$	Proportional Coefficient of PID controller
$\mathbf{K_I}$	Integral Coefficient of PID controller
LDL	Low-Density Lipoprotein
LTI	Linear Time Invariant
LV	Left Ventricle
MCU	Micro-Controller Unit
OS	Operating System
OP-AMP	Operational Amplifier
PDF	Probability Density Function
%HRR	Percentage of Heart Rate Reserve
PI	Proportional - Integral
PID	Proportional - Integral - Derivative
RRI	R-R Interval of ECG signal
RRI STD	Standard Deviation of R-R interval
SBP	Systolic Blood Pressure
$\mathbf{\dot{V}O_2 max}$	Maximal Oxygen Uptake
VT	Ventilatory Threshold

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Abstract

Design and Implementation of Intelligent Fitness Management (IFM) System based on Personalized Exercise Guidance for Obesity

Yeon Sik Noh

Dept. of Biomedical Engineering

The Graduate School

Yonsei University

This thesis presents an intelligent fitness management (IFM) system based on personalized exercise guidance for efficient and direct reduction of obesity and evaluates the changes in obesity-related factors through a comparison with existing exercise methods.

Obesity not only causes cardiovascular and metabolic diseases but also induces complications such as hypertension and diabetes, so its management and treatment are highly important. Obesity has a close interrelationship with physical activity, so increasing physical activity through exercise is very efficient at reducing obesity. Obesity is reduced more efficiently by using both aerobic and resistance exercise; determining the optimal exercise intensity control technique is necessary because an obese person may perceive the

same exercise to be stronger in intensity than a normal-weight person. The exercise method should also be combined with a systematic exercise management system to inspire continuous participation and induce interest in exercise. Thus, this thesis designs an IFM system based on an integrated database server for systematic exercise management and obesity reduction. A statistical model is presented that uses the R-R interval (RRI) and R-R interval standard deviation (RRI STD) to reflect the perceived exercise intensity of an obese person, and an automatic control system that applies the model is suggested.

The proposed IFM system not only provides a systematic exercise prescription that combines aerobic and resistance exercise but also helps increase interest and participation in exercise through continuous management of physical and exercise information. The embedded automatic exercise intensity control system optimized for the obese provides a more stable and efficient exercise method than existing systems and thus directly reduces obesity. To evaluate the proposed IFM system, a free-exercise group and self-control group using the Polar system were designated as control groups; ex-ante and ex-post comparative analyses were conducted to monitor the variations in body composition, hemodynamics, blood, and exercise variables over 8 weeks of exercise.

In the results, the auto-control group who used the proposed IFM system showed an outstanding reduction in obesity compared with the other groups. With regard to body composition, there were marked decreases in the weight, body mass index (BMI), body fat percentage (%body fat), abdominal fat percentage (%abdominal fat), and subcutaneous fat mass. With regard to hemodynamics, the resting heart rate (HRrest) and pressure rate product showed significant decreases. With regard to blood variables, there were significant decreases in hormones and enzymes that signal conditions for lipometabolism (total cholesterol/high-density lipoprotein (HDL) cholesterol, triglyceride in serum), glycol

metabolism (fasting insulin levels, insulin resistance), and hepatic metabolism (alanine transaminase in serum, γ-glutamyltrasferase). Meaningful improvements were shown in fitness-related exercise variables such as cardiopulmonary endurance (maximum oxygen uptake, $\dot{V}O_2max$), muscular endurance, and body flexibility. The proposed IFM system was confirmed to inspire higher and more continuous participation than the other exercise methods.

Based on the results in this thesis, the proposed IFM system can provide a personalized optimal exercise prescription to reduce obesity and induce exercise participation for continued effectiveness. If that system can be applied in obesity management centers or fitness clubs, it should help reduce the prevalence of obesity and related diseases, which are increasing seriously at present.

Key words: obesity, automatic control, integrated fitness management system, statistical control model, body composition, hemodynamics, blood variable, exercise variable, exercise participation

Chapter 1

Introduction

1.1 Risk of obesity and necessity of exercise

The overweight/obese population is increasing with enormous speed due to the decrease in physical activity from improved quality of life, industrialization, and increases in energy intake from the Westernization of eating habits [1-3]. Overweightness/obesity not only causes cardiovascular abnormalities such as left ventricle (LV) structure changes and diastolic dysfunction [4-7] but also induces complications from all kinds of metabolic disorders such as hypertension and diabetes. Therefore, overweight/obese populations have particular management needs [8-9]. Recently, governments and academia have recognized obesity as a disease, and multilateral approaches are being taken for its treatment and prevention [10, 11].

Obesity has an intimate interrelationship with physical activity. According to a Korean national health and nutrition examination survey in 2009 (Table 1.1), the rates of physical activity have been decreasing every year except for physical activity of vigorous intensity; in particular, the physical activity of the over-19 age group has noticeably decreased compared to that of the over-65 age group [12]. Future trends for the increase in obesity prevalence can be predicted from these results: obesity will continue to increase in young people.

Table 1.1 Trends in practice rates of physical activity

Intensity	Age (yr)	‘05	‘07	‘08	‘09	’07-‘09
Vigorous intensity	19+	15.2	13.9	17.1	17.9	16.8
	65+	7.0	7.0	10.4	8.9	9.1
More than Moderate intensity	19+	18.7	9.9	14.5	13.4	13.2
	65+	13.9	8.0	12.1	12.4	11.4
Moderate intensity	19+	29.6	21.1	25.9	26.3	25.1
	65+	18.8	14.0	19.4	18.8	18.1
Walking	19+	60.7	45.7	46.9	46.1	46.3
	65+	54.6	46.8	49.9	47.1	48.2

* From Korean national health & nutrition examination survey [12].

Numerous obesity-related studies have recommended exercise as a regular physical activity for reducing and preventing obesity [13-19]. Regular exercise not only helps improve cardiovascular functions, musculoskeletal functions, immunity, and homeostasis functions [20-26] but also improves the body composition and metabolic functions [27-31]; thus, exercise is the most efficient method for treating and reducing obesity in conjunction with dietary methods.

1.2 Existing exercise methods to reduce obesity

The first suggested exercise method for obesity was regular aerobic exercise. This helps improve most human functions but is limited in making and maintaining a balanced body in terms of fitness management together with obesity treatment. To overcome these limitations, combining aerobic exercise with resistance exercise was suggested. Resistance exercise does not have a major effect on direct weight control and decrease in body fat mass but can help more efficiently reduce obesity by increasing fat-free mass and activating fat oxidation action than aerobic exercise alone [32-37].

Although these exercise methods exist, most obese people do not know the appropriate exercise intensity suitable to their individual fitness condition, so they often may give up exercising or exercise the wrong way. Inappropriate exercise intensity can cause side effects or risk injuries [22]. Thus, new methods for providing an appropriate exercise method have been suggested.

Exercise methods with regular intervention can provide regular exercise habits and appropriate exercise intensity to obtain a positive effect on obesity reduction [38, 39]. However, there are limits to active participation in exercise, and expecting the optimal exercise effect is hard because the exercise intensity is based on average statistical data, not personalized data.

Exercise methods based on an automatic control system to provide the optimal exercise intensity have been suggested [40-43]. However, these systems not only are confined to aerobic exercises using treadmills but also have limited applicability to the obese, who have different physical characteristics than normal-weight persons, because their emphasis is on the optimal automatic control to reach the target exercise intensity as soon as possible.

1.3 Identifying the problem and objectives of thesis

Existing exercise methods to reduce obesity are definitely effective; however, they do not provide optimal exercise methods for the obese. To reduce obesity efficiently, a system that combines aerobic exercise with resistance exercise is needed along with biofeedback to determine a personalized intensity for each kind of exercise. This thesis presents the design and validation of an optimal personalized fitness management system for obesity reduction that meets these needs.

Chapter 2

Literature Review

2.1 Overview

This chapter describes the background literature for the design of an intelligent fitness management (IFM) system to reduce obesity. First, the exercise prescription theory for exercise method and management is described. Second, existing methods for obesity reduction are explained. Third, the biofeedback-based automatic control system theory is explained. Finally, the necessity of optimal exercise intensity control is discussed.

2.2 Exercise prescription theory

2.2.1 Fundamentals of exercise prescription

Exercise prescriptions are used to improve fitness, maintain fitness by reducing risk factors of chronic diseases, and prevent accidents during exercising. Because these purposes are based on individual interests, health necessities, diseases, and so on, not all exercise programs have the same effects on all people. Thus, the basic purpose of exercise prescription is to provide a specific effect to an individual person [44, 45].

Exercise prescription is determined by four principles: *individuality*, or considering the individual distinct characteristics (gender, age, developmental stage, fitness level, health condition, competence level, psychological characteristics, etc.); *overload*, or providing a load that somewhat exceeds the physiological stimulus level to pursue a continuous exercise effect; *progressive load*, or to progressively increase the quality and quantity of the load during the exercise period; and *specificity*, or to conduct exercise suitable to the purpose and body region because the effects of each exercise are confined to the functions of each applied body region [44, 46, 47].

2.2.2 Components of exercise prescription

An exercise prescription must propose an exercise and the intensity, duration, and frequency. Significant factors that must be considered make up the components of exercise prescription.

An exercise prescription comprises qualitative and quantitative components [44, 48]. Qualitative components include exercise type according to exercise purpose and exercise intensity according to individual fitness level. Setting the individual anaerobic threshold (AT) level as the exercise intensity is known to be effective at fitness management and disease improvement [49]. Quantitative components include the duration, frequency, and period of the exercise. The exercise duration is inversely related to the exercise intensity, and proper assignment of the qualitative and quantitative components plays an important role in determining a personalized exercise prescription.

2.3 Existing treatment methods for obesity

2.3.1 Dietary therapy

Dietary restriction is a very important element in obesity management. The human body obtains most of its energy from outside; this energy is created by eating or drinking food. A balanced diet is needed to maintain life and fitness; obese people should particular take care in the kinds and amounts of food they eat. These points have been noted in many studies on the treatment and management of obesity [50-53].

However, while dietary restrictions can increase the functions of insulin resistance and parameters of metabolic syndrome, etc., they may also decrease fat-free mass together with body fat [51] and increase low-density lipoprotein (LDL) cholesterol, which is the main cholesterol transduction molecule in blood [54]. Therefore, regular exercise combined with dietary restriction has become the main recommendation recently [1, 37, 52].

In addition to dietary restrictions, drugs are also being developed to treat obesity; however, not only is it difficult to solve the fundamental obesity problem with this approach, but utilizing drugs for obesity reduction is restricted due to the reported effects on the human body [56].

2.3.2 Interventions in diet and exercise

As obesity management has become entwined with social issues, interest in exercise methods and food regulation for the treatment and reduction of obesity has increased. However, having individuals perform those methods on their own is difficult because objective evaluations of health conditions are limited at present.

Numerous studies have suggested methods for food regulation and exercise through regular intervention [38, 39, 57, 58]. Wilson et al. [38] reported that combining group-based exercise and self-regulated intervention has a positive effect on social cognition, body composition, and strength; Goran et al. [57] emphasized both diet and physical activity and reported that both were helpful to the treatment and prevention of obesity. Long-term lifestyle intervention has been reported to be an efficient method for losing weight and follow-up management/maintenance of weight [58, 59], practical lifestyle intervention is known to motivate improvements in body type and active living habit to reduce obesity more than simple advice [60].

2.3.3 Fitness guide systems

Although obesity management through intervention has many merits as discussed above, it is limited in providing more systematic and direct exercise for the obese. Various studies have proposed fitness guide systems to establish personalized optimal exercise environment for the obese. Barrera et al. [61] presented the system *ZuRoutine*, which provides a personalized exercise routine, diet, and music playlist; Pei-yon and Zhuying [62] presented a personalized health management service system that includes an operating system and hardware layer, middleware and database layer, application layer, portal layer, and client layer; and Lim et al. [40] presented a context-aware fitness guide system that changes the exercise type, frequency, intensity, etc. through context awareness according to individual exercise goals. These systems can provide personalized optimal exercise prescription; however, they are limited in application to varying individual physical conditions during exercise.

With this background, research on automatic control systems based on varying bio-signals (e.g., heart rate) during exercise has progressed briskly. In particular, because heart rate (HR) monitoring is a reliable method of judging the exercise intensity in real time [63], most studies have presented automatic control systems based on biofeedback models using HR [42, 64-66]. These automatic control systems were designed so that the HR would optimally reach the target HR at the appropriate exercise intensity; they were reported to provide more effective exercise to users than exercise conducted through intervention [52, 67, 68]. These methods provided an optimal method to reach the target exercise intensity (e.g., target HR); however, adapting to exercises is difficult due to the drastic changes in the initial exercise intensity of the transient system response because the exercise intensity condition perceived by the user is not considered, and these systems may cause users to give up on exercise.

2.4 Automatic control system theory based on biofeedback

2.4.1 Introduction of feedback control system

The basic ingredients of a control system can be described by three components:

① Objectives (inputs or actuating signal *u*) of control

② Control-system components

③ Results or output-controlled variables *y*

The basic relationship among these three components is shown in Figure 2.1; in general, the objective of the control system is to control the outputs in some prescribed manner by the inputs using elements of the control system [69].

Figure 2.1 Basic components of control system [69].

The feedback control system is known as a closed-loop system due to the feedback element. This system can be more accurate and more adaptive due to the link or feedback from the output to the input of the system compared with open-loop systems, which cannot affect input using the output of the system. To obtain more accurate control, the controlled signal y should be fed back and compared with the reference input; an actuating signal proportional to the difference in the input and output must be sent through the system to correct the error [69]. Figure 2.2 shows a block diagram of the feedback system and elements used in the control system.

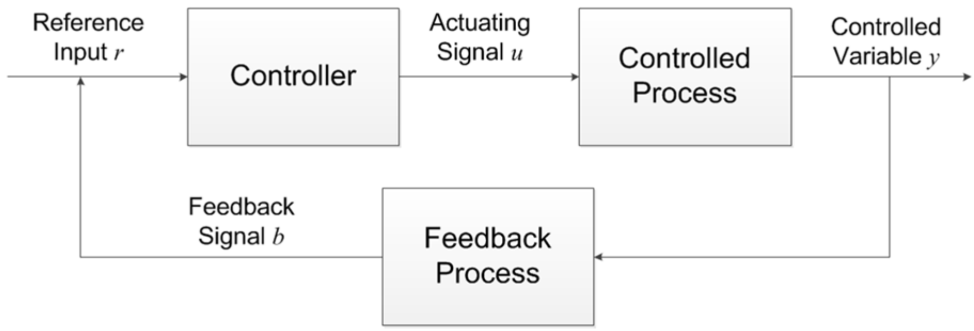


Figure 2.2 Block diagram and elements of closed-loop control system.

2.4.2 Effects of feedback control system

In general, feedback is used to reduce the error between the reference input and system output; however, feedback control is more complex and significant than that. The reduction in system error is merely one of many important effects [69]; this section demonstrates that feedback also affects such system performance characteristics as the overall gain, stability, sensitivity, and external disturbance or noise. Figure 2.3 shows a simple feedback system configuration where r is the input signal, y is the output signal, e is the error, and b is the feedback signal. The parameters G and H may be considered to be constant gains; simple algebraic manipulations show the input–output relation of the system in (2.1). Using this basic relationship of the feedback system structure, some significant effects of feedback can be uncovered. The numerical representations in this section are presented in simple static system notation, not a mathematical approach.

$$M = \frac{y}{r} = \frac{G}{1 + GH} \tag{2.1}$$

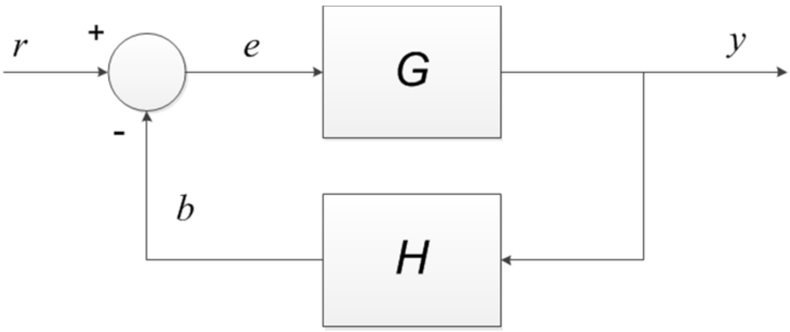


Figure 2.3 Simple feedback system configuration.

The feedback affects the overall gain on a control system. As shown in (2.1), feedback affects gain *G* of a non-feedback system by a factor of *1 + GH*. The feedback, as shown in Figure 2.3, is assigned a minus (–) sign, so this system is said to have a *negative feedback* system. In the case of negative feedback, the quantity *GH* may itself include a minus sign, so the general effect of feedback is that it may increase or decrease gain *G*. In a practical control system, the magnitude of *1 + GH* may be greater than 1 in one frequency range but less than 1 in another because *G* and *H* are functions of frequency [69].

If GH = –1, the output of the system is infinite for any finite input; in this case, this system is said to have an unstable control system. In practice, feedback can not only improve stability but also be harmful to stability. In the case of a negative effect, the system can be stabilized when negative feedback is added. Figure 2.4 shows the feedback system with the added external feedback gain F, which is represented by (2.2).

$$\frac{y}{r} = \frac{G}{1 + GH + GF} \tag{2.2}$$

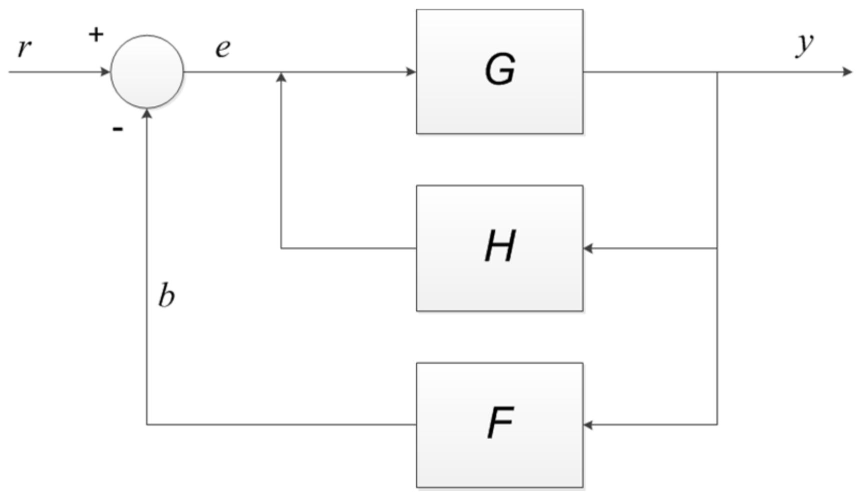


Figure 2.4 Simple feedback system with two feedback loops.

In the design of a control system, sensitivity considerations are often important because the properties of all physical elements (control factors) that change with the environment are not always considered. In general, a good control system has feedback that affects the sensitivity through changes in control factors. As shown in Figure 2.3, the sensitivity of gain of the overall system M to the variation in G is defined in (2.3); by using (2.1), the sensitivity function is written as (2.4). According to (2.4), if GH is a positive constant, the magnitude of the sensitivity function can be made arbitrarily small by increasing GH providing the system remains stable [69].

$$S_G^M = \frac{\partial M/M}{\partial G/G} = \frac{\text{perentage change in } M}{\text{perentage change in } G} \tag{2.3}$$

$$S_G^M = \frac{\partial M}{\partial G}\frac{G}{M} = \frac{1}{1 + GH} \tag{2.4}$$

Although the effect of feedback on external disturbance or noise is greatly dependent on where these external signals occur in the system, most feedback can reduce the effect of disturbance or noise on the system performance. When noise n is added between gain G_1 and gain G_2, as shown in Figure 2.5, the output of the system can be represented as (2.5). The noise component n in (2.5) is reduced by the factor $1 + G_1G_2H$ if G_1G_2H is greater than unit (1); the system then stays stable.

$$y = \frac{G_2}{1 + G_1G_2H}n \tag{2.5}$$

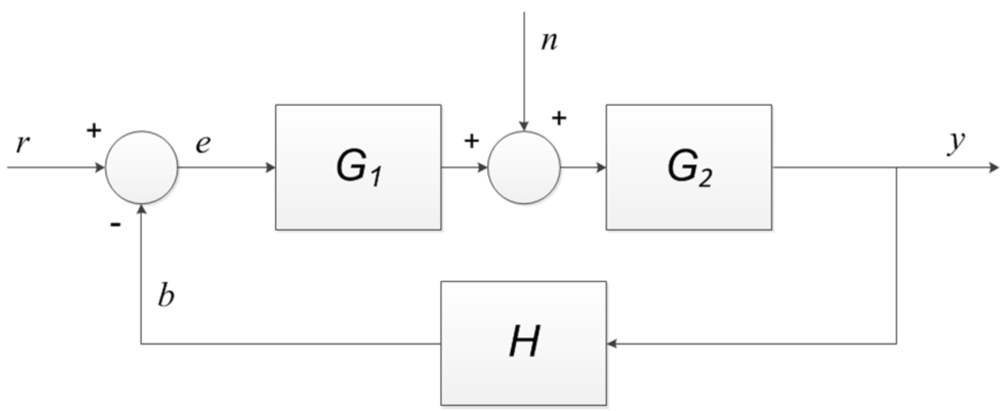


Figure 2.5 Simple feedback system with noise signal.

2.4.3 Design of feedback control system with PI controller

The proportional–integral (PI) controller is a kind of proportional–integral–Derivative (PID) controller that is widely used in the control systems of all industries; it essentially has the characteristics of a low-pass filter. The proportional component plays the role of reducing the error directly between the given input through the feedback system and the output of the system. The integral component minimizes the ripple phenomenon of the error that occurs by producing a signal proportional to the time integral of the input of the controller. Figure 2.6 is a block diagram of a prototype second-order system with a series PI controller. The transfer function of this PI controller is expressed by (2.6).

$$G_c(s) = K_P + \frac{K_I}{s} \tag{2.6}$$

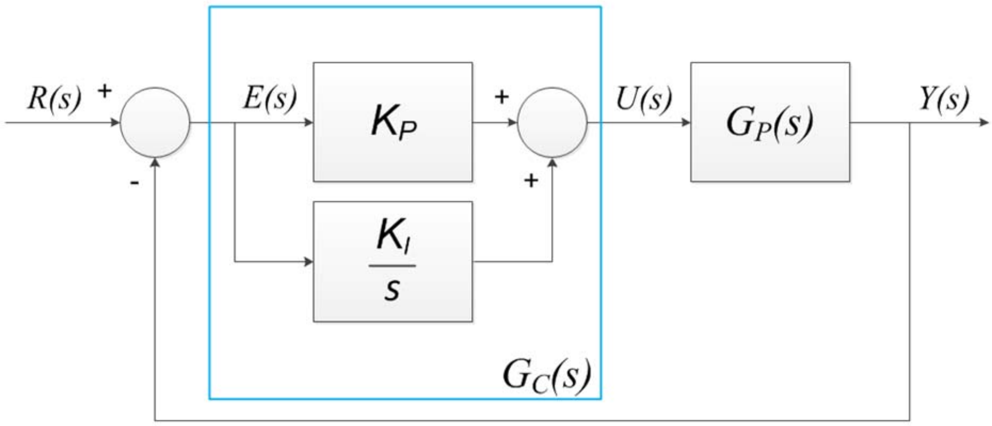


Figure 2.6 Feedback control system with PI controller.

By using (2.6), an operational amplifier (op-amp) circuit is realized with circuit elements, as shown in Figure 2.7 [69]. Figure 2.7 is represented by two op-amps; the transfer function of the system shown in Figure 2.7 is equal to (2.7). When compared with (2.6), the changes in the P coefficient (K_P) and I coefficient (K_I) are as shown in (2.8).

In general, for a given K_P, an efficient PI controller selects K_I that is smaller than K_P. As shown in (2.8), because K_I is inversely proportional to the value of the capacitor, K_I should not be too small or the op-amp circuit implementation would be too large for an efficient and stable PI controller design [69].

$$G_c(s) = \frac{E_o(s)}{E_{in}(s)} = \frac{R_2}{R_1} + \frac{R_2}{R_1 C_2 s} \tag{2.7}$$

$$K_P = \frac{R_2}{R_1}\ , \qquad K_I = \frac{R_2}{R_1 C_2} \tag{2.8}$$

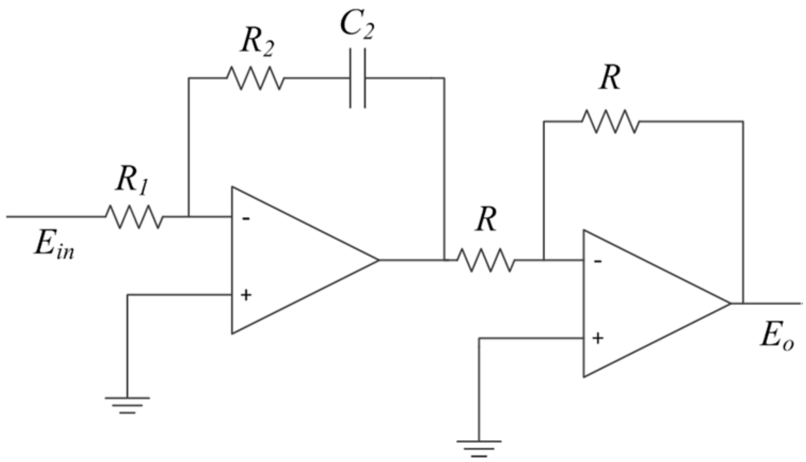


Figure 2.7 Op-amp circuit realization of PI controller.

2.4.4 Robust PI controller design via numerical optimization approach

Most control systems in real plants operate under a wide range of operating conditions, so robustness is an important characteristic of the feedback system [70]. A control system based on feedback can be stabilized against all operating conditions when employing an internal model-based PI or PID tuning method [70-72]. However, this method provides a very slow response to load disturbances of lag-dominant processes because of the pole-zero cancellations inherent in the design methodology [70, 73]. Another approach is tuning the PI or PID controller by the gain and phase margin specifications [70, 74, 75]. Both the gain and phase margin act as important measures of robustness; in particular, the phase margin is related to the damping of the system, so it can also serve as a performance measure of the control system [70, 76]. Numerical progress has been made in improving the performance of PI and PID control systems [77].

In order to apply a numerical approach, a process model is required. One of the most widely used process classes is characterized by an aperiodic response [70]. This important category of industrial systems can be represented by a first order plus dead time (FOPDT) model [70, 78-80]:

$$G_P(s) = \frac{ke^{-t_0 s}}{1 + \tau s} \tag{2.9}$$

Note that the above process model is only used for the purpose of simplified analysis. A simple method is based on analysis of the open-loop step response. Thus, the parameters of the process model in (2.9) are obtained as follows: k is the final value of the step response of the process, t_0 is the process transport delay, and τ is the process time constant. In this section, only the PI controller design is described.

To design a robust PI controller, the design problem statement must be the priority. Consider the PI feedback control system shown in Figure 2.6, where $G_P(s)$ represents the transfer function of the process model (2.9), and $G_C(s)$ is the transfer function of the standard PI controller. For this control system, the sensitivity function $S(s)$ is defined as follows:

$$S(s) = \frac{1}{1 + G_C(s)G_P(s)} = \frac{1}{1 + L(s)} \tag{2.10}$$

where $L(s) = G_C(s)G_P(s)$ is the open-loop transfer function.

The complementary sensitivity function $T(s)$, which is the transfer function of the closed-loop system, is defined as follows:

$$T(s) = 1 - S(s) = \frac{L(s)}{1 + L(s)} \tag{2.11}$$

The quantity $|T(j\omega)|_{s=j\omega}$ represents the input–output gain at a frequency of $2\pi/\omega$. For a PI controller, this gain is equal to that in the low frequency domain: that is, the steady state error is equal to zero. The quantity $M_P = max_\omega|T(j\omega)|$ is the peak magnitude of the frequency response of the closed-loop system [70] and is related to the overshoot for the step response of the closed-loop system. To impose a good transient response, the following condition is necessary [70]:

$$M_P \leq M_P^+ \tag{2.12}$$

where $M_P^+ > 1$ is the upper bound of the maximum of the complementary sensitivity function. The following constraint is also required:

$$D \leq D^+ \tag{2.13}$$

where D is the first overshoot of the step response and D^+ is the upper bound value of this overshoot. A lower bound pseudo-damping factor δ_m can then be introduced; this is related to the upper bound of the first overshoot by the following relation [70]:

$$\delta_m = \frac{|\ln(D^+)|}{\sqrt{\pi^2 + \ln(D^+)^2}} \tag{2.14}$$

According to Di Stefano et al. [81], the relation between M_P^+ and the lower bound pseudo-damping factor δ_m is as follows [70]:

$$M_P^+ = \frac{1}{2\delta_m\sqrt{1 + (\delta_m)^2}} \tag{2.15}$$

For a good transient response, the following is required:

$$\delta \ \geq \ \delta_m \tag{2.16}$$

where δ is the pseudo-damping factor of the closed-loop system. The quantity $1/|S(j\omega)|$ represents the distance between the Nyquist curve of the open-loop transfer function $L(s)$ and the critical point -1 at a frequency of $2\pi/\omega$. This means that the minimum distance represents a good measure of the stability margin [70].

Based on the above theory and formulas, the PI controller can be numerically optimized using the FOPDT process model. In the standard PI controller shown in Figure 2.6 and the process model in (2.9), the open-loop system is given by

$$L(s) = \frac{k(1 + K_P T_i s)e^{-t_0 s}}{T_i s(1 + \tau s)} \tag{2.17}$$

where $T_i = 1/K_I$. Using the approximation $e^{-t_0 s} \approx 1/(1 + t_0 \mathrm{s})$, the polynomial characteristic of the closed-loop system is given by

$$\rho(s) = s^3 + \frac{t_0 + \tau}{t_0\tau}s^2 + \frac{1 + K_P k}{t_0\tau}s + \frac{k}{T_i t_0 \tau} \tag{2.18}$$

$$\rho(s) = (s + a)(s^2 + 2\delta\omega_0 s + \omega_0^2)$$

where

$$a = \frac{t_0 + \tau}{t_0\tau} - 2\delta\omega_0 \tag{2.19}$$

$$K_P = \frac{(\omega_0 + 2a\delta)\omega_0 t_0\tau - 1}{k}$$

$$K_I = \frac{a{\omega_0}^2 t_0\tau}{k}$$

The closed-loop stability imposes $a > 0$, which is true if

$$\frac{t_0 + \tau}{\delta\omega_0 t_0\tau} > 2 \tag{2.20}$$

The above inequality is satisfied for

$$\frac{t_0 + \tau}{\delta\omega_0 t_0\tau} = b \tag{2.21}$$

where $b > 2$ [70].

Finally, the optimization problem is written by considering $\delta = \delta_m$ to achieve a good transient response, good stability margin, and good robustness as follows:

$$\max_{b>2}\left\{\min_{w}|1 + L(j\omega, b|\right\} \tag{2.22}$$

$$L(s) = \frac{k(1 + K_P T_i s)e^{-t_0 s}}{T_i s(1 + \tau s)}$$

$$\omega_0 = \frac{t_0 + \tau}{b\delta_m t_0\tau}$$

$$a = \frac{t_0 + \tau}{t_0 \tau} - 2\delta_m \omega_0$$

$$K_P = \frac{(\omega_0 + 2a\delta_m)\omega_0 t_0 \tau - 1}{k}$$

$$K_I = \frac{a{\omega_0}^2 t_0 \tau}{k}$$

2.4.5 Existing feedback control system for exercise on treadmill

Existing commercial treadmills are designed for users to control the speed and gradient and provide the exercise intensity that users want; thus, they help include exercise into part of daily life. However, these systems are still limited in terms of providing personalized appropriate exercise intensity. Numerous studies have tried to design a system that can be controlled for each individual through feedback of personal physiological information during exercise.

Lichtenstein et al. [41] used a hip tracker based on a PID controller and suggested a system that can provide stable exercise for visually impaired patients through feedback on the distance of the tracker. However, this system only uses the position information of user and cannot obtain physiological information at all, so it is limited in providing efficient exercise.

Kawada et al. [65] suggested a servo-controller framework based on a PI controller to regulate varying HR during treadmill exercise. They optimized the feedback parameters via a computer simulation in order to achieve a quick and stable HR response after estimating the averaged transfer function from the speed command to the HR. However, because they tried to optimize their control system by changing fixed coefficient values, their system is limited in efficiently dealing with variations in HR, which can be generated during exercise.

Su et al. [64] suggested a fuzzy-based PI controller having a very efficient control performance with an unknown structure or nonlinear operation systems for robust control of control parameters according to variations in HR during exercise. They used two input parameters for fuzzy control: the last error and the difference between the last and present errors. Using these input parameters, they controlled the output of their system by setting the present error state to four fuzzy sets; however, their system is also limited when handling the numerous factors that vary HR during exercise.

In practice, the variation in HR during exercise has a nonlinear characteristic. Hence, some studies have suggested that control systems based on a nonlinear control model would be able to regulate HR much more robustly [42, 66, 82]. These systems can reduce the error of system control through an efficient response against nonlinear variations of bio-signals that are not considered in the linear control model. These systems definitely affect the target exercise intensity desired by the user; however, they do not consider individual perceived exercise intensity conditions and variations in the autonomic nervous system (ANS), which vary during exercise. Therefore, particular attention is needed when these systems are applied to patients with diseases (e.g., obesity) and not normal-weight people.

2.4.6 Necessity of optimized exercise intensity control for obesity

Because the suggested treadmill control systems to date mainly researched normal-weight people, they are limited in application to patients with diseases. For the obese, they perceive the same exercise as having much greater intensity than normal-weight people with similar cardiopulmonary endurance (maximum oxygen uptake, $\dot{V}O2max$). Furthermore, when exercising, they may find it difficult to adapt or give up exercise entirely if the initial intensity changes drastically in order for them to reach their target exercise intensity. Therefore, it is very important to design a system that can promote continuous exercise participation by the obese and provide a personalized optimal exercise intensity based on the perceived exercise intensity condition during exercise. This thesis proposes a control system that is optimized for the obese (see section 3.4).

Chapter 3

Design of Intelligent Fitness Management (IFM) System

3.1 Overview

This chapter describes the design of an intelligent fitness management (IFM) system based on theory and practice: the overall system configuration, the exercise prescription process for the obese, and an automatic exercise equipment control system using a biofeedback-based PI controller that is optimized for the obese.

3.2 System configuration

The IFM system comprises three main parts: biometric modules and a physical sensor module that measure bio-signals and exercise information during exercise in real-time; an exercise equipment system that controls the exercise equipment or helps operate them through information obtained from bio-signals; and an integrated database server embedded with individual physical and fitness information, management of bio-signals measured during exercise, exercise information measured from the exercise equipment, and the exercise prescription scenario. Figure 3.1 shows the configuration of the IFM system designed in this thesis.

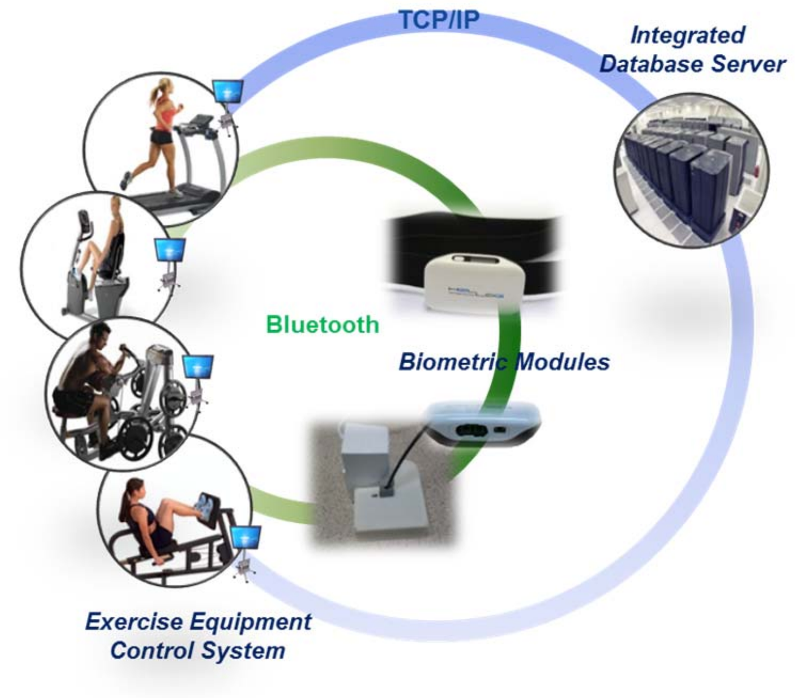


Figure 3.1 System configuration.

3.2.1 Biometric modules and physical sensor module

Biometric modules play two roles in the IFM system: recognizing the user and monitoring the fitness condition by measuring bio-signals and providing significant feedback factors to the exercise equipment control system. There are two types of biometric modules: bio-signal measurement modules measure bio-signals such as the electrocardiogram (ECG), skin temperature, respiration, and activity; and the electromyogram (EMG) measurement module measures the EMG. Only the former type can perform the user recognition function.

The bio-signal measurement module was designed using a 32-bit microprocessor unit (MCU) ARM-Cortex M3 STM32F103RE (STMicroelectronics, Switzerland), as shown in Figure 3.2. This module can measure one-channel ECG, HR, R-R interval (RRI), respiration, skin temperature and activity signals. The ECG signal is measured by two conductive textile electrodes attached to the chest belt and is sampled at 360 Hz. The activity signals are measured by an MMA7361L (Freescale Semiconductor, USA) three-axis accelerometer and sampled at 20 Hz along the X, Y, and Z axes. The data of the three-axis activity signals are useful in estimating the energy expenditure during exercise. The variance in the skin temperature signal during exercise is measured by an MLX90615 (Melexis, Belgium) infrared temperature sensor for humans and sampled at 1 Hz. The respiration signal is measured by transforming the variation in the thoracic volume caused by respiration to the variation in the impedance signal. To measure the impedance signal, a constant current of 1 mA and a 100 kHz sine wave were injected into the thorax of upper body using the same two conductive textile electrodes for measuring the ECG signal. The four-electrode method is widely used to measure the impedance signal, but the two-electrode method was used in this thesis to utilize the electrodes measuring the ECG signal. The design was based on the single source and sink method.

This module can recognize the user by the Bluetooth media access control (MAC) address embedded in it; identification data are transmitted to an integrated database server together with the bio-signals measured during exercise. The current body condition with respect to the given exercise prescription is monitored through bio-signals measured during exercise; in particular, the RRI signal is fed back to the exercise equipment control system for the user to reach his or her exercise target. This contributes to maintaining stable and efficient exercise by providing an automatic personalized exercise intensity according to the current body condition of the individual.

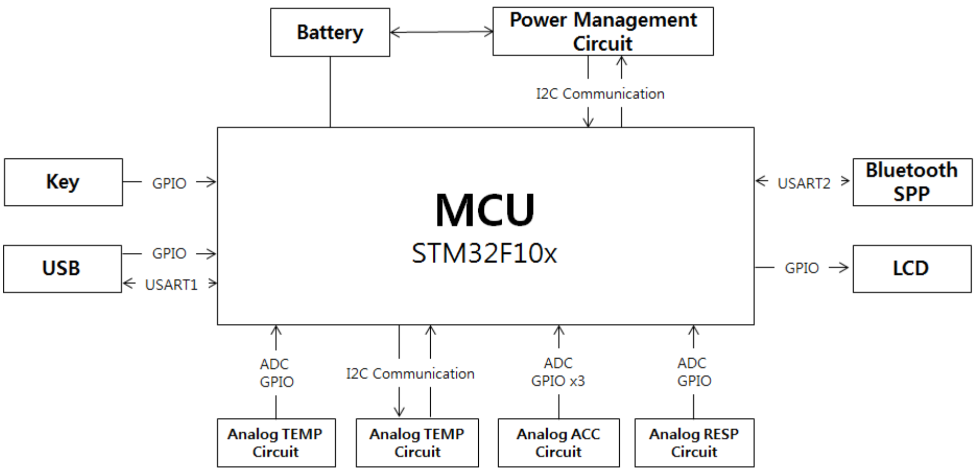


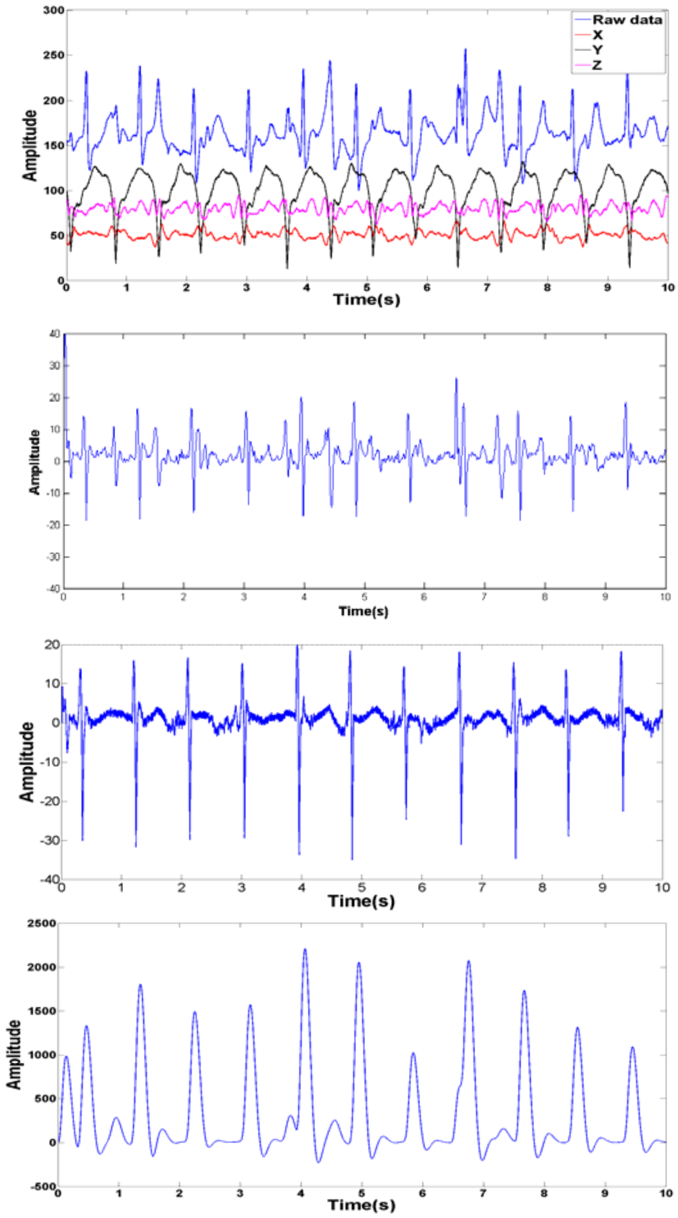
Figure 3.2 Block diagram of biometric module.

Figure 3.3 shows the measured bio-signals (one-channel ECG and three-axis activity signals) during treadmill exercise at 12 km/h and the signal processing process for detecting the QRS complex from the ECG signal. To detect the QRS complex, the ECG signal—which is unaffected by moving artifact noise—is extracted from the raw ECG signal by an adaptive filter (filter order: 5) based on the normalized least mean square (NLMS) algorithm, as shown in (3.1). Figure 3.4 shows the structure of the algorithm for moving artifact noise rejection; V_x, V_y, and V_z are the activity signals with respect to the X, Y, and Z axes, respectively. The A bandpass filter (cutoff frequency: 10–30 Hz) is used to emphasize the frequency range of the QRS complex.

$$e(n) = d(n) - \boldsymbol{\hat{w}}(n)\boldsymbol{u}(n) \tag{3.1}$$

$$\hat{\mathrm{w}}(\mathrm{n}+1) = \hat{\mathrm{w}}(\mathrm{n}) + \frac{\tilde{\mu}}{\|\mathrm{u}(\mathrm{n})\|^2}\mathrm{u}(\mathrm{n})\mathrm{e}^*(\mathrm{n})$$

In (3.1), M is the number of taps (i.e., filter length: 512); $\tilde{\mu}$ is the adaptation constant ($0 < \tilde{\mu} < 2$, $\tilde{\mu} = 0.99$); n is the time index; $\boldsymbol{u}(n)$ is the M × 1 tap input vector at time n; $\boldsymbol{\hat{w}}(n)$ is the estimated tap-weight vector at time step n; *d(n)* is the measured ECG signal; and *e(n)* is the ECG signal after rejecting the moving artifact noise.



(a)

(b)

(c)

(d)

Figure 3.3 Signal processing for QRS complex detection: (a) raw ECG and activity signals, (b) signal with motion artifacts removed using activity information, (c) signal with high-frequency external interferences removed, and (d) detected QRS complex.

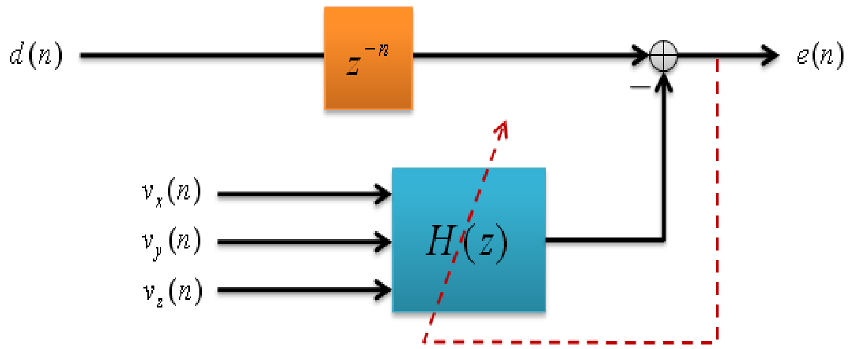


Figure 3.4 Structure of algorithm for moving artifact noise: *d(n)*, *e(n)*, and *H(z)* are the measured ECG signal, ECG signal after moving artifact noise is rejected, and adaptive filter, respectively.

Activity signals are utilized to estimate the energy expenditure (calorie consumption) during exercise. The calorie consumption is estimated by (3.2), which utilizes variations in the three-axis accelerometer vector as independent variables. The IFM system was designed to determine the calorie consumption through the square root of accumulated variations of each accelerometer vector every 10 s.

$$\text{Calorie Consumption (kcal)} = (0.00051 \times \mathrm{x}) + 0.51 \tag{3.2}$$

$$\mathrm{x} = \sqrt{\mathrm{X_{axis}}^2 + \mathrm{Y_{axis}}^2 + \mathrm{Z_{axis}}^2}$$

In this thesis, an EMG module for monitoring the resistance exercise and physical sensor module for detecting the resistance exercise load (intensity) were developed to manage resistance exercise. The physical sensor module is a tension sensor module; it can detect the weight and repeat count of resistance exercise equipment. The EMG module was designed based on the same framework for the bio-signal measurement module presented above (Figure 3.5). The tension sensor module was designed based on an 8-bit MCU ATmega128L (Atmel, USA), as shown in Figure 3.6. The tension sensor K-100 (Lorenz Messtechnik, Germany) is located between the weight of a resistance exercise equipment and cable, and the tension sensor module is mounted on top of the weight of the resistance exercise equipment.

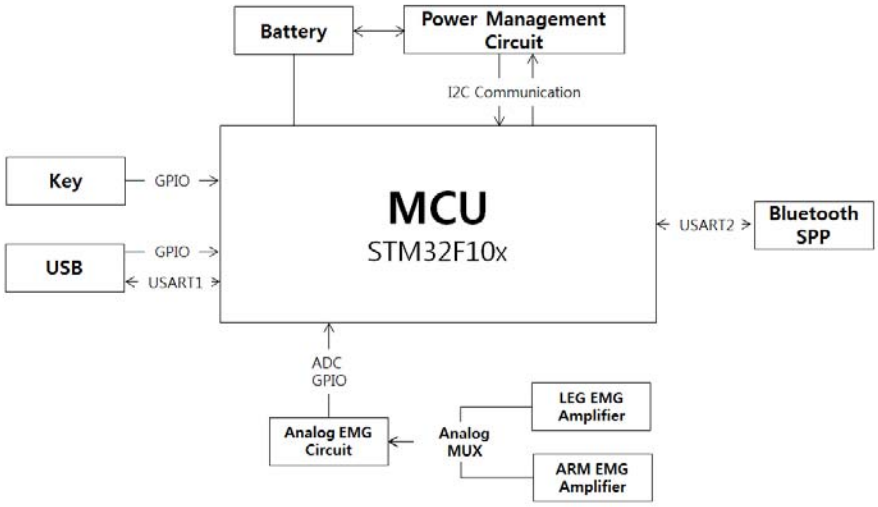


Figure 3.5 Block diagram of EMG measurement module.

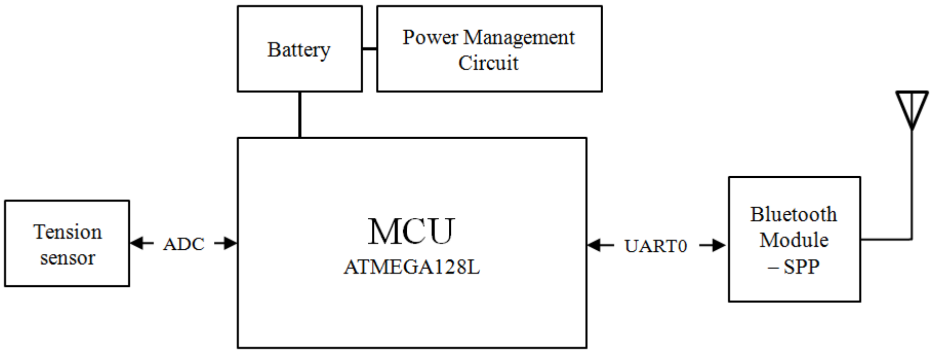


Figure 3.6   Block diagram of tension sensor module.

As shown in Figure 3.7, the EMG signal is measured by attaching Ag–AgCl electrodes at the following locations for each exercise of major muscles: ① bench press; ② lateral pull-down; ③ abdominals; ④ arm curls; ⑤ shoulder press; ⑥ triceps; ⑦, ⑧ leg curl; and ⑨ leg press. The EMG signal is sampled at 360 Hz and utilized to estimate the muscle fatigue rate.

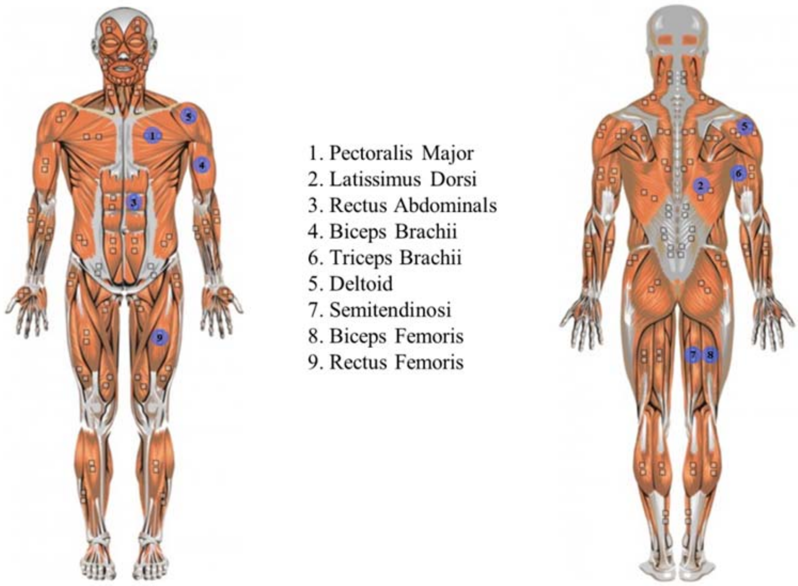


Figure 3.7 Locations for EMG signal measurement.

The tension sensor measures the real weight while the user exercises and counts the number of performed repetitions using the tension signal. Figure 3.8 shows the output of the tension sensor according to the variation of each weight; the linearity of the output of the tension sensor was verified by increasing the weight in 5 kg increments (Figure 3.9). The output of the tension sensor is put through a low-pass filter (cutoff frequency: 1 Hz) for accurate data analysis.

The muscle fatigue rate is calculated at the end of each set through fast Fourier transform (FFT) of the measured EMG signal using by [83]. The rate is estimated from the average EMG frequency at the start of each set of resistance exercises to the end; the maximum muscle fatigue is determined when the muscle fatigue rate decreases by more than 15%. The muscle fatigue rate display on the graphic user interface (GUI) of the exercise equipment control system changes from green to red depending on the muscle fatigue condition: the redder it becomes, the higher the muscle fatigue rate.

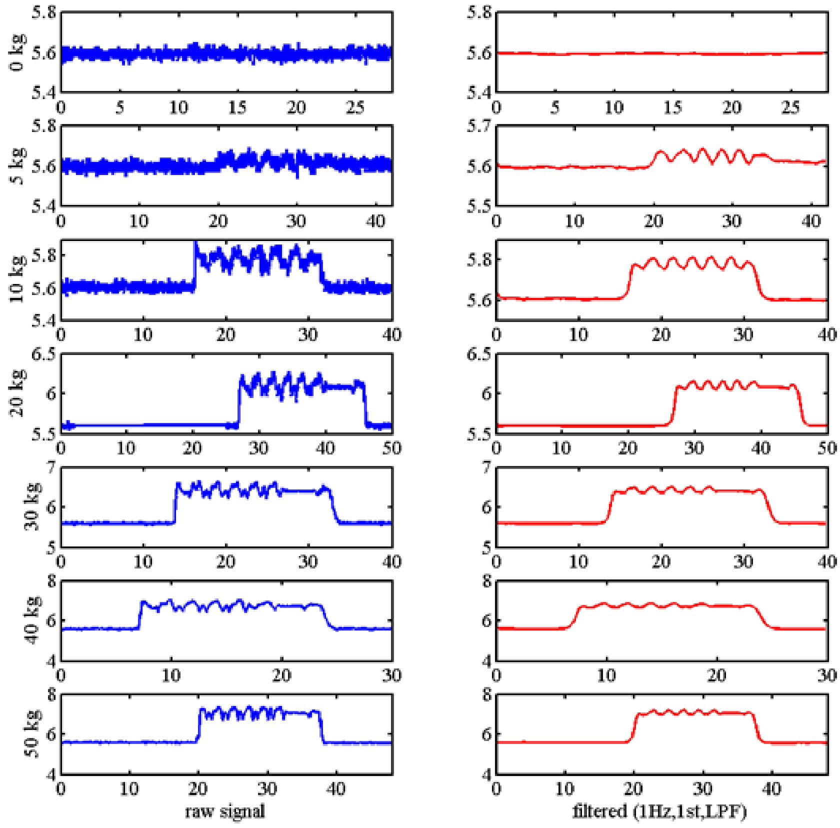


Figure 3.8 Outputs of tension sensor according to different weights.

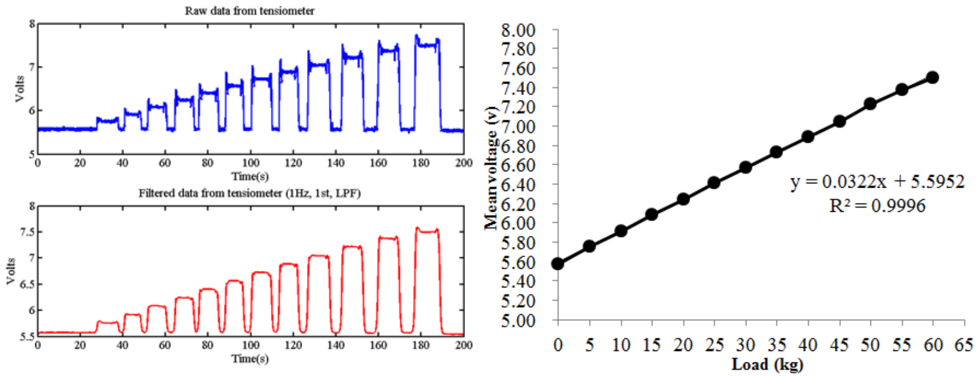


Figure 3.9 Linearity validation of output of tension sensor.

3.2.2 Exercise equipment control system

The exercise equipment control system comprises a mini-PC and 17″ touch monitor. The mini-PC is a barebones PC (Viako, South Korea) that supports WiFi communication; the touch monitor is connected to it. A GUI program based on the Windows operating system (OS) is installed in the mini-PC for user convenience and IFM system operation; this program performs various functions such as user recognition, reception and display of bio-signals and exercise data, user management through connection to the integrated database server, and display of appropriate individual exercise intensity and automatic control of exercise intensity using bio-signals.

The GUI program for treadmill exercise displays the ECG signal, activity signals, respiration signal, current HR, current skin temperature, target HR, current speed, calorie consumption, and exercise time. The GUI program for resistance exercise displays the EMG signal, images for respiration tracking, prescribed and performed exercise information (weight, repeat count, set number), and muscle fatigue rate.

3.2.3 Integrated database server

The integrated database server was developed based on Oracle (Oracle, USA), which is a representative server program [84]. This server system contains an exercise prescription scenario for the personalized IFM system of the obese; it was designed to manage and store individual exercise, physical, and fitness information. To prescribe exercise and update performed exercise information, it comprises database fields for all parameters utilized in the IFM system; database tables are created according to the classified parameters. The integrated database server system networks with all exercise equipment in the IFM system using TCP/IP communication.

3.3 Exercise prescription process for obesity

The exercise prescription process for obesity comprises exercise capacity assessment, pre-exercise assessment and health-related fitness test, and exercise prescription scenario for obesity.

The aerobic exercise capacity (VO2max) is estimated by a prediction method based on real-time detection of the ventilator threshold (VT) using the modified Balke protocol [85] proposed by Kim [86]; the resistance exercise capacity (1 repetition maximum (RM)) is estimated by using (3.3), which was proposed by Wathen [87], for each major muscle.

$$1\ \mathrm{RM} = \frac{Load}{(0.488 + 0.538 \times \exp(-0.075 \times Repitions))} \tag{3.3}$$

During the pre-exercise assessment, the blood pressure, height, weight, body composition, and resting HR (HRrest) are measured. During the health-related fitness test, the muscular strength (hand grip strength), muscular endurance (sit-ups), body flexibility (sit-and-reach), body balance (stork balance stand), explosive muscular strength (vertical jump), and body agility (reaction time) are measured with the Helmas system (O2run, Korea).

The exercise period, intensity, and time of the exercise prescription scenario for obesity are determined according to the target body fat percentage (%body fat), as shown in Figure 3.10. All exercise prescription information is supplemented with the theory and practice recommended by the American College of Sports Medicine (ACSM) for application to the IFM system. In particular, the exercise intensity provided by the IFM system is set using the percentage of heart rate reserve (%HRR) proposed by Karvonen et al. [88]; setting the exercise intensity using %HRR has not only been verified to be efficient but is also widely used in fields for exercise prescription [89]. In this thesis, the individual target HR is decided by (3.4); the IFM system uses this to provide a personalized exercise intensity for obesity. The maximum heart rate (HRmax) is calculated by the equation for “220-age,” which was proposed by Haskell and Fox [90].

$$\begin{aligned}\text{Target Heart Rate} \\ &= \big((\text{Maximum Heart Rate} - \text{Resting Heart Rate}) \times \%\text{Intensity}\big) \\ &+ \text{Resting Heart Rate}\end{aligned} \tag{3.4}$$

The target %body fat is set to 25% as the default; this can be changed according to the goals of the user in the integrated database server. The exercise prescription components of aerobic exercise for obesity are calculated by the process shown in Figure 3.10. For the exercise period, D is set to 500 kcal as the default; this can also be changed in the same manner as setting the target %body fat. The basic program for resistance exercise is three sets of 10 RM, 10 times; it is designed to provide resistance exercise to different regions every day, as shown in Table 3.1.

Table 3.1 Resistance exercise program

	1st	2nd	3rd
Upper body	BP	AB	AC
	PD	TC	SP
Lower body	LP	LC	(Alternately)

* BP: Bench Press, PD: Lat Pull Down, AB: Abdominal, TC: TriCep, AC: Arm Curl, SP: Shoulder Press, LP: Leg Press, LC: Leg Curl.

1. Set Target body fat $=$ 25% (default)

2. Calculate Target weight $=$

$$\frac{\text{Weight of body fat}}{1-\frac{\text{Target body fat (\%)}}{100}}$$

3. Weight for reduction (A) $=$ Present weight $-$ Target weight

4. (A) kg $\times$ 2.2 $=$ (B) lb (1lb $=$ 3,500 kcal)

5. (B) $\times$ 3,500 kcal $=$ (C) kcal

6. Set exercise period $=$ (C) $\div$ (D) kcal $=$ (E) days

7. Set exercise intensity $=$ 40 $-$ 50 %HRR (default)

8. Target $\dot{V}O_2$ (F) $(ml \times min^{-1} \times kg^{-1}) =$

$$\frac{\text{\%Intensity}}{100} \times (\dot{V}O_2\,\text{max} - 3.5) + 3.5$$

9. (F $-$ 3.5) $(ml \times min^{-1} \times kg^{-1}) \times$ (A) $(kg) \div 1000$

$$= \text{(G)}\ (L \times min^{-1})$$

10. (G) $(L \times min^{-1}) \times 5 =$ (H) $(kcal \times min^{-1})$

11. Set exercise time (I) $=$ (D) $(kcal) \div$ (H) $(kcal \times min^{-1})$

Figure 3.10 Exercise prescription scenario for obesity.

3.4 Automatic exercise intensity control system

3.4.1 Purpose of exercise equipment control system

The proposed IFM system is intended to reduce obesity and was designed to consider the physical characteristics of the obese. The obese not only have a markedly lower exercise capacity but also perceive the same exercise as higher intensity than normal-weight people; hence, the perceived exercise intensity condition must be monitored in real-time by the control system.

Other existing systems provide optimized control for a personalized exercise intensity. However, most focus on shortening the time to reach the target exercise intensity and maintaining it; hence, they may make it difficult to continue or cause the obese to give up because of the perceived gap in exercise intensity. This thesis proposes a new control method based on monitoring the perceived exercise intensity in real-time and considering the physical characteristics of the obese.

3.4.2 Design of biofeedback system based on PI controller

The exercise equipment control system uses biofeedback and was designed based on a PID controller. The PID controller is a representative single-output linear time invariant (LTI) system; the advantage of this system is that a controller can easily be developed without control model. As noted in section 2.4, PID stands for proportional–integral–derivative; its performance depends on each coefficient of P, I, and D.

Because controllers used in industrial environments generally aim to reach the target stage with accurate control and minimal error in the least amount of time, PID controllers are usually used as they combine the advantages of PI and PD controllers. However, reaching the target HR based on physiological data during exercise requires control that elicits the maximum effect of exercise safely rather than precise control. The derivative part of the PID controller minimizes the occurrence of overshoot by inhibiting variations in the error signal; in this thesis, a PI controller was developed by removing the derivative part of the PID controller.

The PI controller was designed by designating the current HR as the feedback element of the controller; exercise is maintained at the target HR by reducing the error between the data fed back from the output of control system and the individual target HR. The P coefficient directly controls the exercise intensity (i.e., speed of treadmill); the I coefficient reduces the errors of the controller controlled by the P coefficient in steady state. However, fixed coefficient values are generally limited in being able to respond efficiently to variation in the HR and perceived exercise intensity condition.

The optimal control method for the obese should be designed towards obtaining the maximum exercise effect rather than reaching the target condition as soon as possible. In order to apply the optimal control method for the obese, the physiological model according to the given exercise intensity needs to be predicted. The ideal output of HR according to the exercise intensity has the form FOPDT, as noted in section 2.4.4. Based on this model, theoretical considerations for setting the optimal control coefficients can be predicted through a mathematical approach. The optimal control method for the obese should minimize overshoot of the control system and also needs to minimize the pseudo-damping factor of the control system to obtain a good transient response and good stability.

This thesis proposes statistical models to provide the optimal exercise intensity for the obese. These models were considered under theoretical conditions and modified to overcome the weakness of the existing PID controller, which has fixed coefficients. These models consider physical conditions, which vary exercise intensity, and were designed to control the P and I coefficients dynamically in real-time based on RRI and R-R interval standard deviation (RRI STD), which reflect the perceived individual exercise intensity according to the given exercise intensity.

3.4.3 Statistical model for PI coefficient control

RRI and RRI STD are important factors for confirming the perceived exercise intensity in real-time. RRI is closely related with ANS [91-93]; it confirms the mechanism of the body state that occurs spontaneously with external physical and mental stimuli. Variations in these parameters according to exercise intensity are considered preferentially.

First, the statistical characteristics of RRI and RRI STD that occur at each exercise intensity for varying treadmill speeds are analyzed. The one-channel ECG signal is measured as the treadmill speed is increased: rest (0 km/h), 3 km/h, 6 km/h, and 9 km/h. RRI and RRI STD are extracted from the ECG signal. The measured data was hypothesized to obey the normal distribution; the data are modeled as a bivariate Gaussian probability density function (PDF). Based on that model, the pattern of cross-correlation distribution is classified according to the variation in exercise intensity by analysis of the cross-covariance matrix. The cross-correlation value is the degree of correlation between two separate random variables. If both variables increase, the covariance value becomes a positive number; if only one increases, it becomes a negative number. If the covariance value is zero (0), the two random variables have no correlation with each other. The typical equation of covariance matrix is shown in (3.5); (3.6) was used in this thesis to analyze the covariance between two separate variables based on (3.5).

$$\mathrm{COV}[X] = \sum \tag{3.5}$$

$$= E[(X - \mu)(X - \mu)^T]$$

$$= E\begin{bmatrix} E[(X_1 - \mu_1)(X_1 - \mu_1)] & \cdots & E[(X_1 - \mu_1)(X_N - \mu_N)] \\ \vdots & \vdots & \vdots \\ E[(X_N - \mu_N)(X_1 - \mu_1)] & \ldots & E[(X_N - \mu_N)(X_N - \mu_N)] \end{bmatrix} = \begin{bmatrix} \sigma_1^2 & \ldots & c_{1N} \\ \vdots & \vdots & \vdots \\ c_{1N} & \ldots & \sigma_N^2 \end{bmatrix}$$

$$\mathrm{COV(X, Y) = E[(X - E[X])(Y - E[Y])^T]} \tag{3.6}$$

Figure 3.11 presents the results of cross-correlation analysis at each speed in the form of a full covariance matrix. The left end of Figure 3.11 shows the result at 9 km/h; the results at 6 km/h, 3 km/h, and rest (0 km/h) are toward the right direction. These results correlate with existing studies: increasing the exercise intensity decreases RRI STD [92, 93], and a decrease in RRI is related with increased HR from increasing exercise intensity.

As shown in Figure 3.11, the cross-correlation distribution at each speed was confirmed to have a mutuality-independent interrelationship. Based on this finding, both RRI and RRI STD were used as control factors for the controller in this thesis. These control factors were utilized to adjust the P and I coefficients in real-time based on the RRI and RRI STD distribution ranges according to exercise intensity.

To analyze the distributions of RRI and RRI STD according to exercise intensity more clearly, they are remodeled in the form of a diagonal covariance matrix in Figure 3.12.

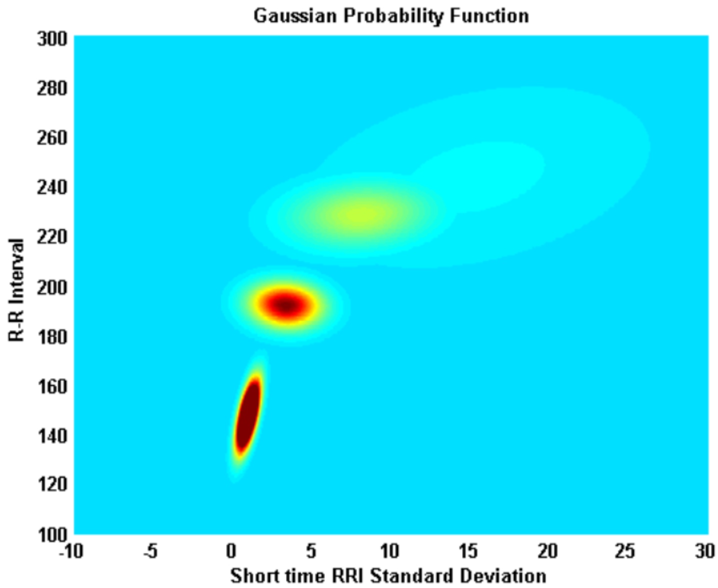


Figure 3.11   Result of full covariance matrix between RRI and RRI STD.

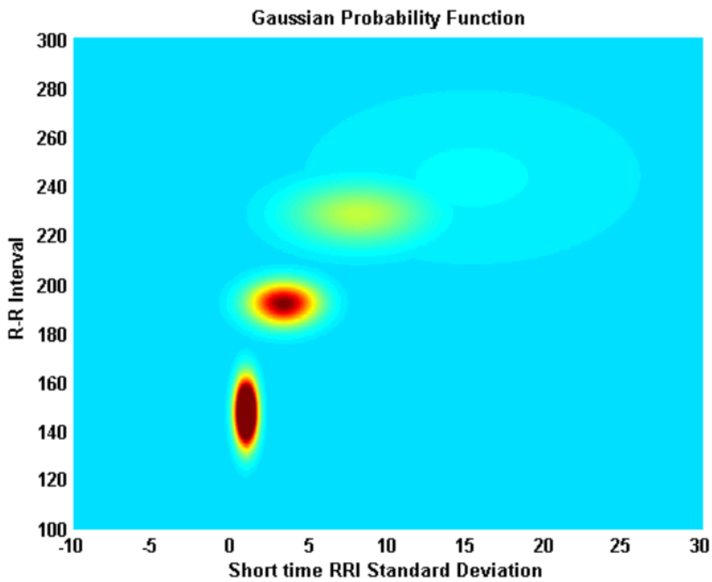


Figure 3.12   Result of diagonal covariance matrix between RRI and RRI STD.

Figure 3.12 confirms that a higher exercise intensity brings RRI STD closer to zero (0); the RRI STD according to exercise intensity is distributed between 0 and 10 at 3–9 km/h, which is widely known to be the generally prescribed exercise intensity. In this thesis, the range of exercise intensity was confined to a maximum of 9 km/h and minimum of 3 km/h; the proposed statistical model of the P coefficient for controlling the exercise intensity directly is limited to this range.

The P coefficient of the PI controller is the proportional factor; it helps determine the exercise intensity. As shown in the distributions of Figure 3.12, an RRI STD value close to 0 means that the perceived exercise intensity condition is higher. On the other hand, a value closer to 10 means that the perceived exercise intensity condition is lower. To provide the optimal exercise intensity for the obese, maintaining a continuous intermediate intensity that is appropriate for the individual needs to be maintained. A control system design that can maintain this intensity during exercise is needed. The direct exercise intensity should be decreased when the perceived exercise intensity condition is much higher and be controlled to limit drastic intensity variations at the early stages of exercise for safe and stable exercise. In this thesis, the function of the P coefficient (K_P) was modeled based on the statistical distribution in Figure 3.12 in the form of a Gaussian distribution function using (3.7), as shown in Figure 3.13. This allowed control of the progressive exercise intensity at the early stages of exercise and provided the appropriate exercise intensity continuously to the end of the exercise.

The control model for the I coefficient (K_I) is shown in Figure 3.14; it was modeled as an integral form of the P coefficient to minimize the error in the steady state caused by variations in the P coefficient model based on exercise intensity and to maintain the target exercise intensity. It was applied by inverting the model of the P coefficient (K_P) against the

Y axis and shifting RRI STD within the range 0–10. The model of the I coefficient (K_I) is explained in (3.8).

$$K_P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \times exp\left(\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right) \tag{3.7}$$

$$\sigma^2 = 1.5, \mu = 5$$

$$K_I(x) = k_I(-x+10) \tag{3.8}$$

$$k_I(x) = \int K_P(x)dx$$

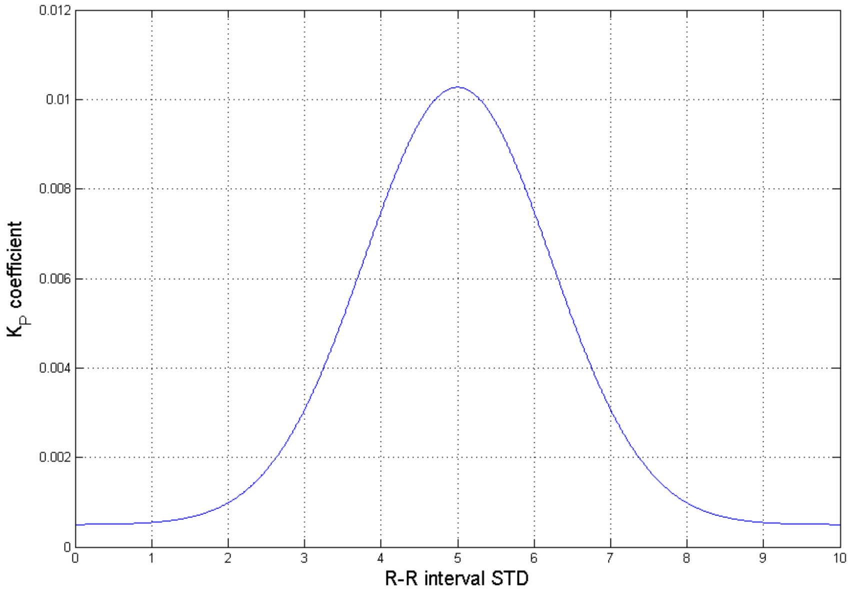


Figure 3.13 Statistical model for controlling P coefficient.

Figure 3.15 shows the block diagram of the proposed PI controller. SP and PV mean the target HR and current HR, respectively. First, the error $(e(k))$ between the target HR and current HR measured during exercise is calculated according to (3.9). The proportional control signal $(u_P(k))$ and integral control signal $(u_I(k))$ are calculated as shown in (3.10). T_i and Δt are the integral constant and time interval, respectively, of the sample collection in (3.10). Equation (3.11) is used to derive the control signal $(\mathrm{u}(k))$ for controlling the exercise equipment. The final control signal $(\mathrm{u}(k))$ is shown in (3.12).

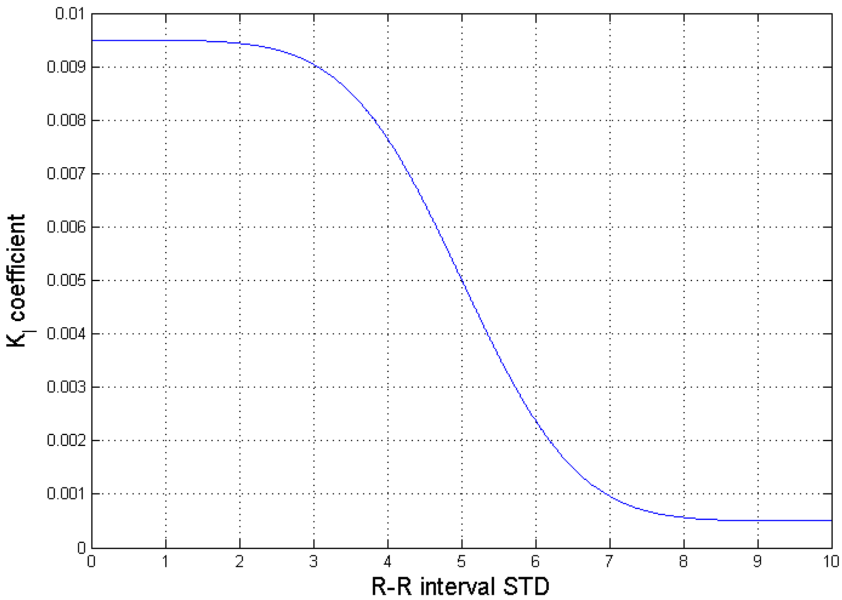


Figure 3.14 Statistical model for controlling I coefficient.

$$\mathrm{e}(k) = SP - PV \tag{3.9}$$

$$u_P(k) = 1 \times e(k), \qquad u_I(k) = \frac{K_c}{T_i}\sum_{i=1}^{k}\left[\frac{e(i) - e(i-1)}{2}\right]\Delta t \tag{3.10}$$

$$u(k) = u_P(k) + u_i(k) \tag{3.11}$$

$$\mathrm{u}'(k) \geq u_{max}, then\ u(k) = u_{max}$$

$$\mathrm{u}'(k) \leq u_{min}, then\ u(k) = u_{min}$$

$$\mathrm{u}(k) = K_c \times e(k) + K_c \times \frac{1}{T_i}\sum_{i=1}^{k}\left[\frac{e(i) - e(i-1)}{2}\right] \quad (3.12)$$

$$K_c\,(x) = \alpha \times \frac{1}{\sqrt{2\pi\sigma^2}} \times exp\left(\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right) + c \quad (3.13)$$

$\sigma^2 = 1.5, \quad \mu = 5, \quad \alpha = 0.03, \quad c = 0.0005$

$$t_i(x) = \beta \times \int K_c\,(x)dx + c \quad (3.14)$$

$$T_i(x) = t_i(-x + 10)$$

$\beta = 0.009, \quad c = 0.0005$

3.4.4 Evaluation of automatic exercise intensity control system

To evaluate the control models of P and I coefficients proposed in this thesis, a test bench program based on LabVIEW™ (NI, USA) was developed. As shown in Figure 3.16, this program was designed to control the exercise intensity on a treadmill based on the proposed coefficient control model. Both the coefficient control model and the states of the P and I coefficients are determined by using the control model according to RRI and RRI STD in real-time, as shown in the upper left of Figure 3.16; bio-signals measured during exercise and bio-signal analysis information are displayed on the lower right. Figure 3.17 shows the result of controlling the exercise intensity appropriately based on the proposed coefficient control model.

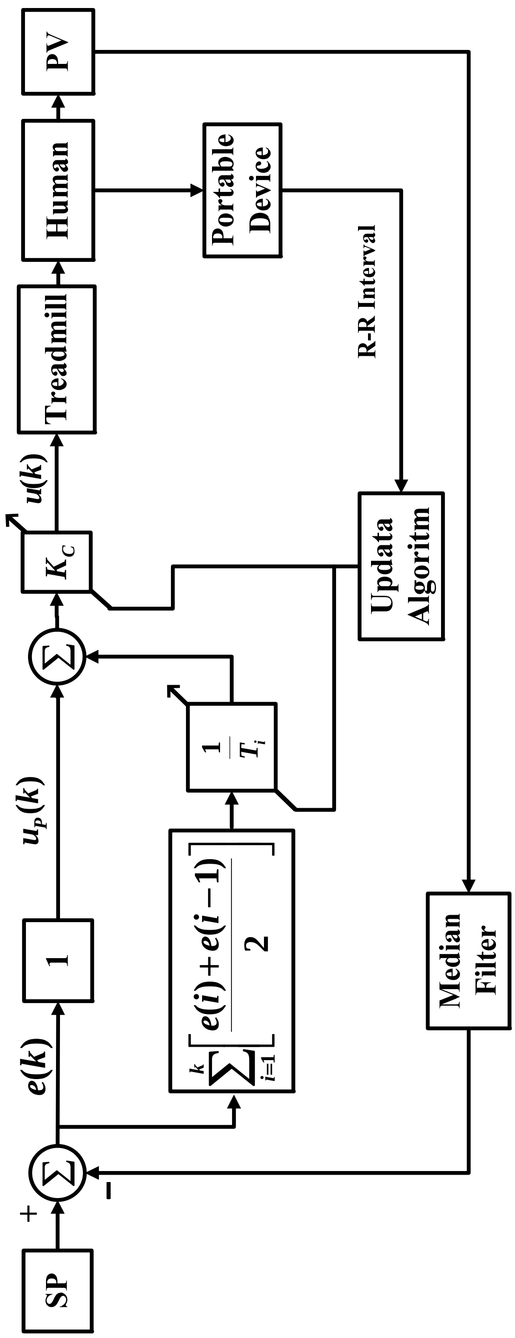


Figure 3.15 Block diagram of PI controller for automatic exercise intensity control of treadmill based on biofeedback.

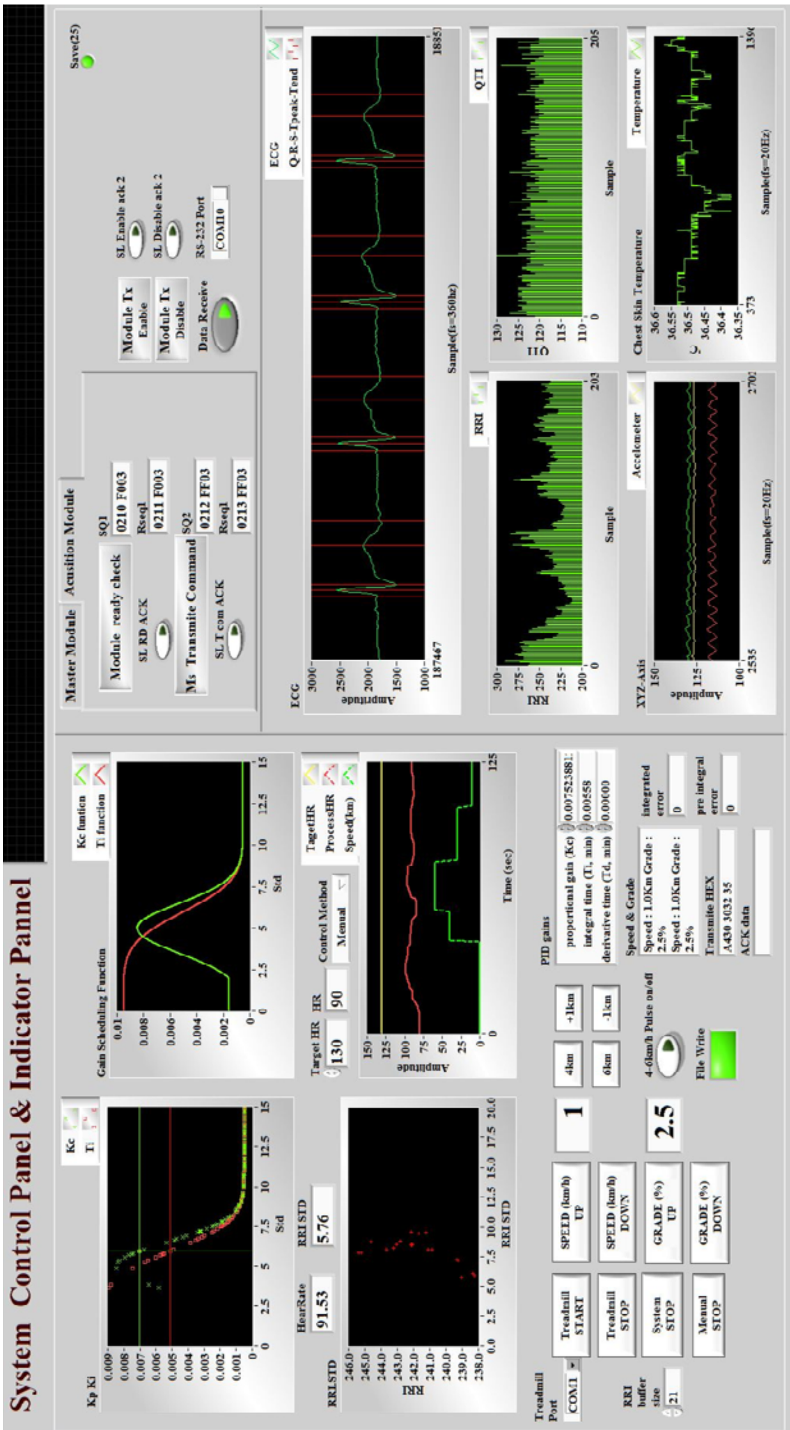


Figure 3.16   Test workbench for automatic exercise intensity control system.

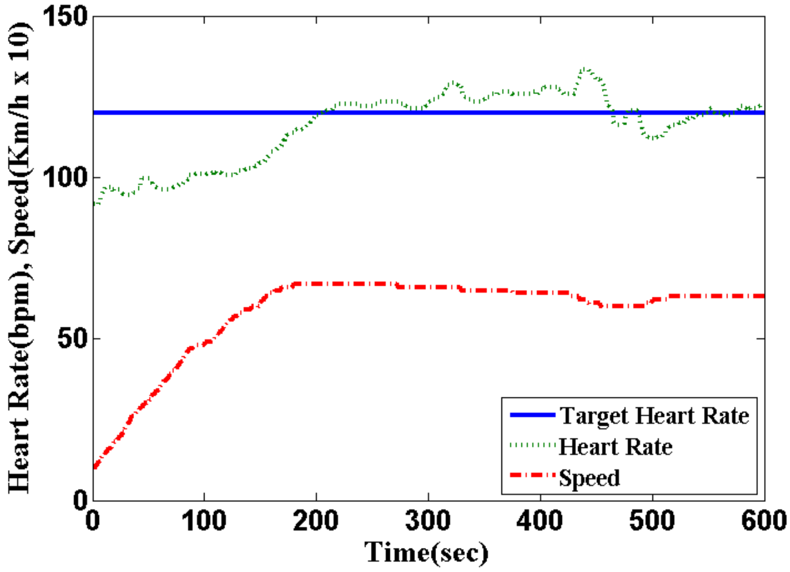


Figure 3.17 HR and speed controlled by dynamic PI coefficient control model.

3.4.5 Automatic exercise intensity control in resistance exercise

The resistance exercise equipment used in the thesis cannot control the weight automatically; hence, it was limited in terms of controlling the exercise intensity the same way as in aerobic exercise. This thesis thus proposes that the exercise intensity be updated based on information on the performed exercise after the end of exercise; in other words, the exercise intensity is not controlled in real-time. If the averaged repetition count for a given three-set exercise is over 12, the next exercise time would use the present weight with an additional 10% weight; this weight depends on the nearest matching weight for each piece of resistance exercise equipment. During resistance exercise, the muscular condition during each set can be monitored through the GUI program display embedded in the exercise equipment control system; this can help in avoiding immoderate exercise.

Chapter 4

Implementation of IFM System for the obese

4.1 Overview

This chapter presents results obtained by implementing the developed IFM system with the obese. The exercise program and data analysis method for the experimental design, selection, and subject group characteristics are described along with the results for verification of the IFM system.

4.2 Subjects

4.2.1 Characteristics of subjects

The subjects in this experiment were recruited based on the selection criteria shown in Table 4.1. The roughly 30 male and 30 female obese subjects were 30–60 years in age and had at least two of the obesity criteria (①, ②, and ③) in Table 4.1. Only voluntary participants were recruited from people who registered at the Wonju Public Fitness Center or Lifetime Health, Exercise & Medicine Center of Yonsei University Wonju College of Medicine. Prior to the experiment, the experiment was explained to the subjects, and all of the subjects signed an experiment participation consent form. All of the experiment processes proceeded with the approval of the Deliberating Committee of Human Test of Yonsei University Wonju College of Medicine (No. 2011-28) [Appendix 1].

Table 4.1 Guidelines for recruiting subjects

Gender	① BMI	② Waist		Standard Weight	③ Comparison with Standard Weight
Male	> 25	90 cm	36 inch	Over 160 cm (Height-100) x 0.9	120-130% Obesity
Female	> 30	80 cm	32 inch	150- 160 cm (Height-150)/2 + 50	Over 130% Morbid Obesity

Table 4.2 shows the subject characteristics. Thirty-six male and 36 female subjects were recruited initially, but nine males and eight females were left off the experiment because

they changed their minds, injuries caused by carelessness during exercise, etc. Section 4.2.2 describes each group in the experiment.

Table 4.2 Subject characteristics

	Free exercise Group	Self-control system Group	Auto-control system Group
Female	9	9	9
Male	9	9	10
Age (years)	48.6±9.1	40.7±8.1	43.4±8.8
Height (cm)	163.4±7.5	165.4±10.0	166.1±7.9
Weight (kg)	75.5±12.1	80.7±11.1	77.3±9.6
BMI	28.2±4.1	29.4±1.9	28.1±3.2
Body fat (%)	31.7±5.4	33.0±4.66	32.0±5.7

4.2.2 Control groups and experimental group

In this experiment, the subjects were divided into two control groups and one experimental group to verify the IFM system. Table 4.3 shows the concept and exercise method for each group. The auto-control system group used the proposed IFM system; the free exercise and self-control system groups were control groups for comparison with the IFM system. The free exercise group literally exercised on their own with no intervention with regard to the exercise time, exercise frequency, and exercise intensity. In the self-control system group, individual exercise prescription information was provided in advance and an exercise program was provided where they could check their own HR during exercise by using the watch-type HR monitor RX800CX SD (Polar, Finland) against the given exercise prescription. Different experimental sites were used for each group, and a blind experiment protocol was put in place so the subjects would not know each other's exercise method.

Table 4.3 Control groups and experimental group

	Negative Control group (Free exercise)	Positive Control group (Self-control system)		Experimental Group (Auto-control system)	
Concept	Free Exercise	Self-control system (aerobic) and ACSM guideline (resistance)		Auto-control system (aerobic + resistance)	
Aerobic exercise		THR Zone (± 10 beats/min) - Out of range → alarming & self-control		IFM System	
Resistance exercise		Self-exercise according to suggested guideline		IFM System	
		Upper-body	Bench press	Pull down	Abdominal
		Lower-body	Leg Extension	Leg Curl	Leg press

4.3 Experimental design

4.3.1 Necessity and purpose

This experiment was designed to verify the IFM system. The IFM system was designed to combat obesity, which has become a big social issue with regard to life quality; the usefulness and superiority of the proposed IFM system was expected to be confirmed through the experiment results.

4.3.2 Exercise program

Different 8-week exercise programs were provided to each group. The free exercise group was provided an exercise program involving exercising on their own without any interference. The self-control and auto-control groups were provided the same exercise program but different approaches towards performing the exercise.

For aerobic exercise, the self-control group was instructed to perform 5 min of warm-up exercise (male: 6 km/h, female: 5.5 km/h) and then exercise on a treadmill at an exercise intensity of 60–70 %HRR according to the watch-type HR monitor RX800CX SD (Polar, Finland). The auto-control group was provided with biometric modules developed in this thesis, and the exercise program was controlled and managed by the IFM system automatically.

The resistance exercises were designed according to the major muscles: chest, dorsal, and abdominal exercises for the upper body and quadriceps, femoral, and knee flexion exercises for the lower body. The self-control group was instructed to exercise at an intensity of three sets of ten repetitions for 10 RM, which was calculated from a test to determine the maximum resistance exercise capacity (1 RM) of each major muscle. The auto-control group was provided a resistance exercise prescription given by the IFM system after the same 1 RM test used for the self-control group. Figure 4.1 shows the experiment progress in practice and Figure 4.2 shows the overall block diagram of the experiment to verify the IFM system.

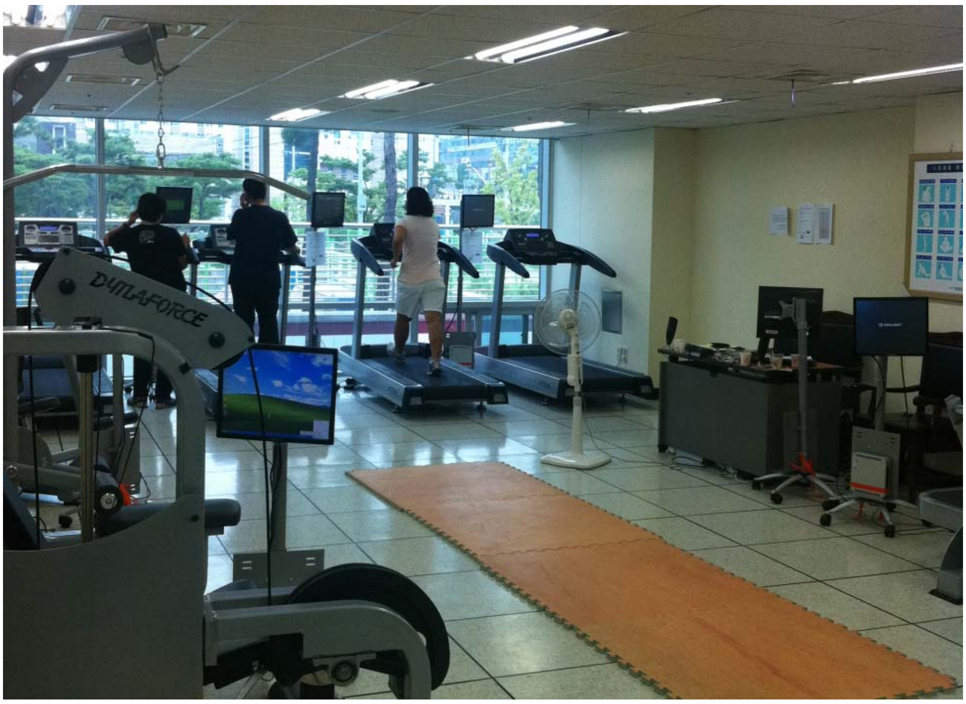


Figure 4.1 Experimental environment for implementation of IFM system.

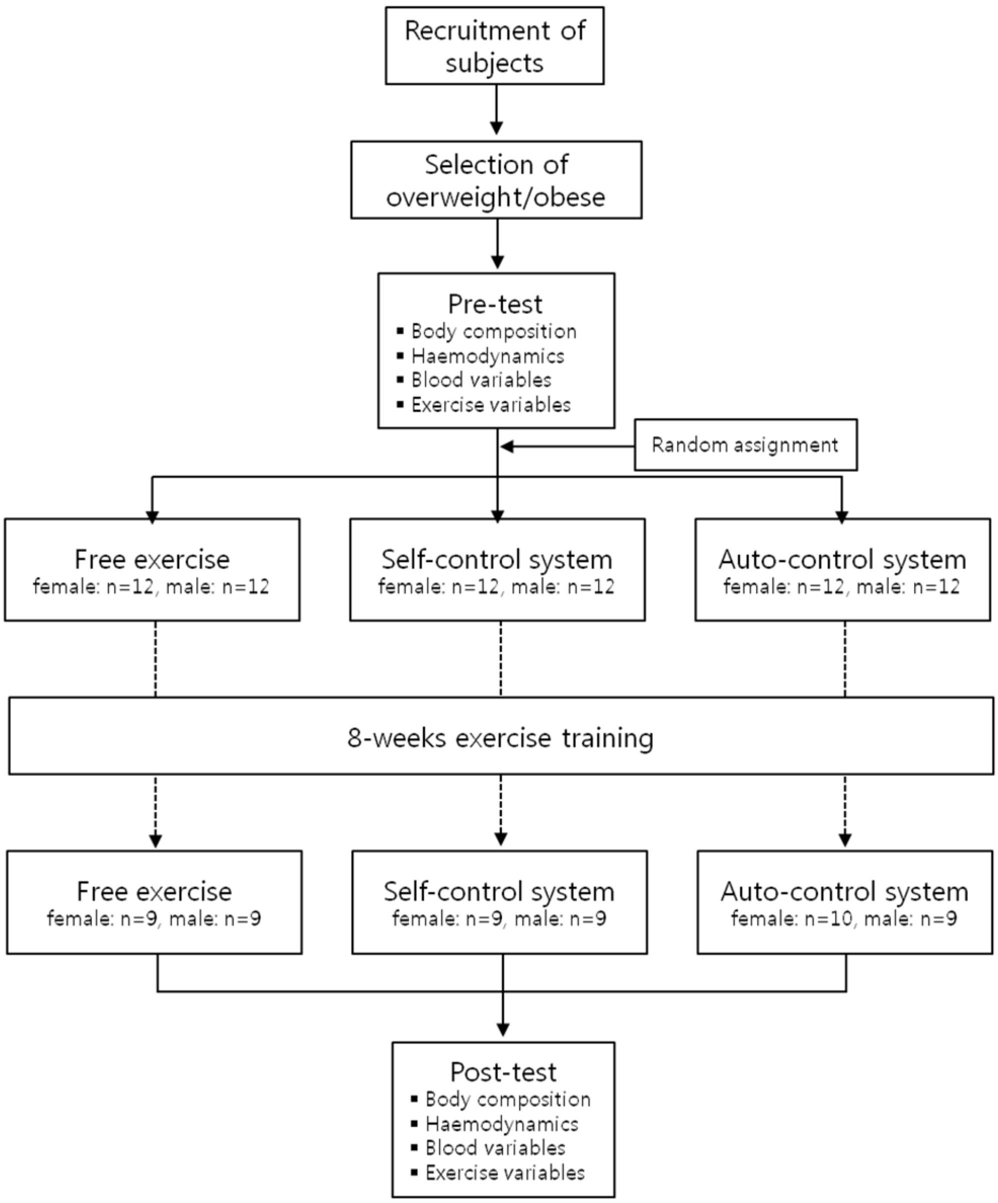


Figure 4.2 Block diagram of overall experimental design.

4.3.3 Examination lists and data analysis methods

The ex-ante and ex-post analyses for each group were compared to evaluate the degrees of improvement in biomarkers. Health-related fitness and metabolic syndrome risk factor tests were conducted. The health-related fitness tests compared the variations in each health-related fitness component: cardiopulmonary endurance ($\dot{V}O2max$), muscular strength (hand grip strength), muscular endurance (sit-up), body flexibility (sit-and-reach), body balance (stork balance stand), explosive muscular strength (vertical jump), and body agility (reaction time). The risk factors of metabolic syndrome were tested by examining the waist, blood pressure, blood sugar, triglyceride, cholesterol, etc. In particular, the variations in body composition, hemodynamics, blood variables, and exercise variables were analyzed. All of the results were represented as mean ± standard deviation; they were analyzed statistically using one-way analysis of variance (ANOVA) to compare the ex-ante and ex-post variation rates in health-related fitness components and metabolic syndrome risk factors.

4.4 Results

Significantly better results were obtained for the health indices of the group using the IFM system than those of the free exercise and self-control groups. The overall results of the ex-ante and ex-post analyses of the free exercise, self-control, and auto-control groups are shown in Tables 4.4–4.6, respectively. To compare the variation in each exercise group, the variation rate in the ex-ante and ex-post comparison of each parameter were used as the analysis criterion rather than the absolute variation.

4.4.1 Variations in body composition components

The auto-control group showed significantly more improvement in the variation rates of the weight, body fat percentage (%body fat), and subcutaneous fat mass compared to the free exercise and self-control groups (Figures 4.3, 4.5, and 4.7). The auto-control group also showed a significantly greater decrease in body mass index (BMI) than the self-control group and a significantly greater decrease in abdominal fat percentage (%abdominal fat) than the free exercise group (Figures 4.4 and 4.6).

In the auto-control group, the weight, waist, and BMI decreased by 3.2%, 3.3%, and 2.4%, respectively. The visceral fat and subcutaneous fat mass decreased by 9.9% and 6.5%, respectively, in terms of components of the body composition. The %abdominal fat and total %body fat decreased by 1.3% and 4.0%, respectively, in terms of the variation in fat distribution according to fat ratio.

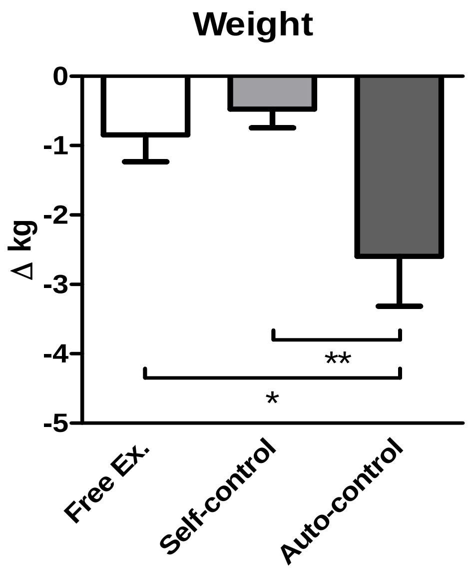


Figure 4.3 Variation rates of weight for each group. * $p < 0.05$, ** $p < 0.01$ compared with auto-control system group.

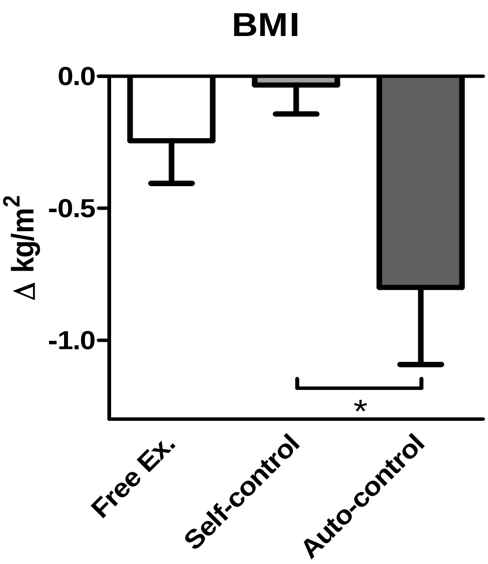


Figure 4.4 Variation rates of BMI for each group. * $p < 0.05$ compared with auto-control system group.

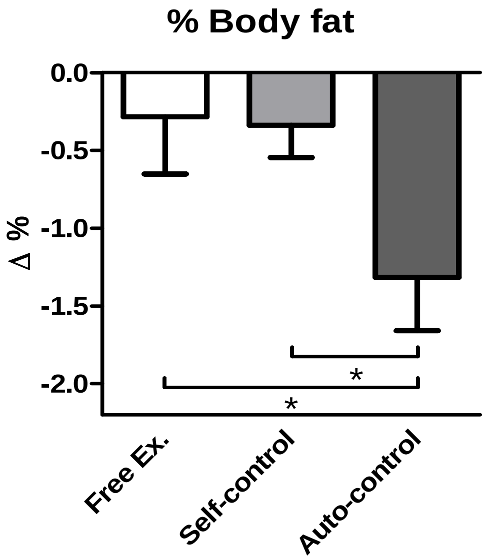


Figure 4.5 Variation rates of %body fat for each group. * p < 0.05 compared with auto-control system group.

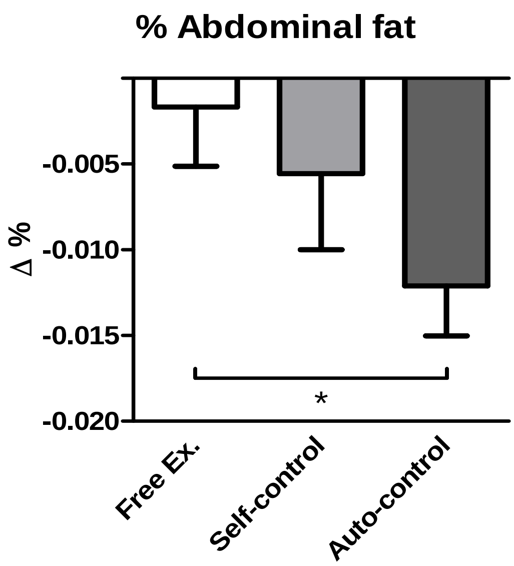


Figure 4.6 Variation rates of %abdominal fat for each group. * p < 0.05 compared with auto-control system group.

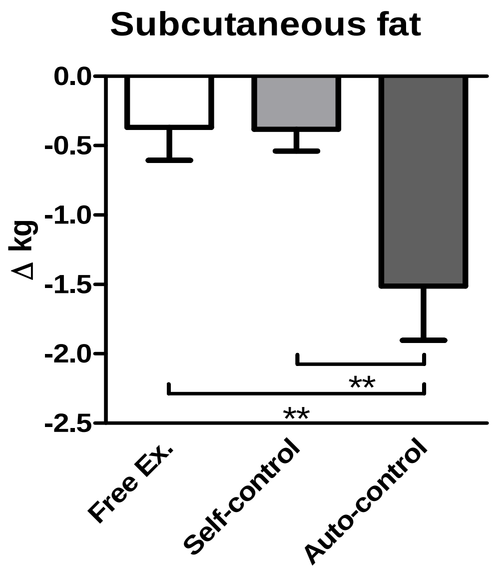


Figure 4.7 Variation rates of subcutaneous fat mass for each group. ** $p < 0.01$ compared with auto-control system group.

4.4.2 Variations in hemodynamics components

The auto-control group showed significant improvements in the variation rates of hemodynamics components such as the resting heart rate (HRrest) and pressure rate product (systolic blood pressure (SBP) × HRrest) compared to the free exercise and self-control groups (Figures 4.8 and 4.9).

As hemodynamics indices, the SBP and diastolic blood pressure (DBP) decreased by 6.8% and 6.0%, respectively, according to the measured resting blood pressure and HR. HRrest also decreased significantly by 9.7%. Exercise management (training) by the IFM system was confirmed to decrease the pressure rate product by 15.3%.

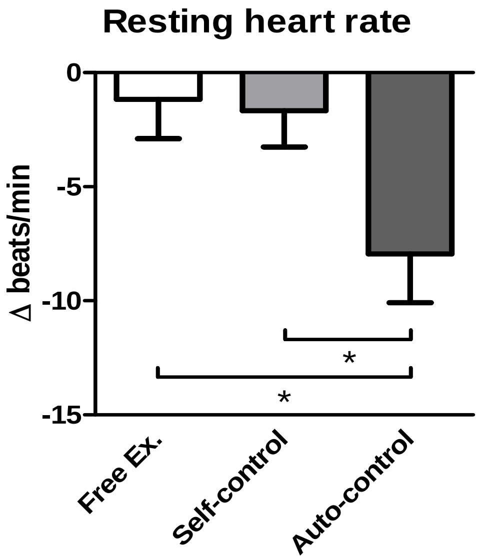


Figure 4.8 Variation rates of resting heart rate for each group. * $p < 0.05$ compared with auto-control system group.

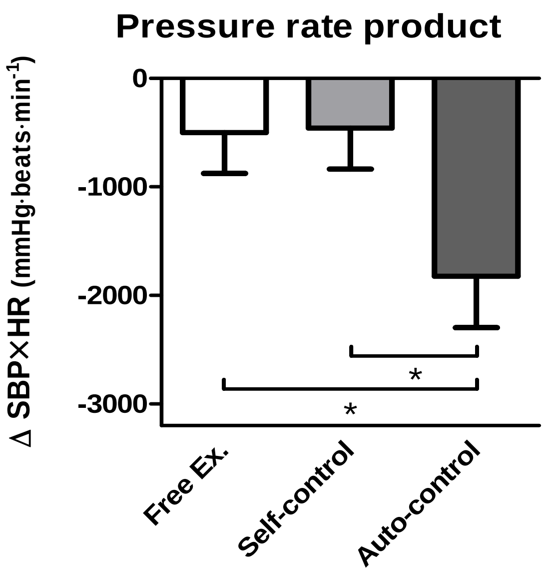


Figure 4.9 Variation rates of pressure rate product for each group. * $p < 0.05$ compared with auto-control system group.

4.4.3 Variations in blood variable components

A comparison of the blood variable components showed significant improvements in the indices of lipometabolism, glycol metabolism, and hepatic metabolism. The auto-control group showed significant decreases in the blood variable indices of lipometabolism—the variation rates of total cholesterol/high-density lipoprotein (HDL) cholesterol and triglyceride in serum—compared to the free exercise and self-control groups (Figures 4.10 and 4.11). The auto-control group showed a significant decrease in the blood variable index of glycol metabolism—fasting insulin level—compared to the free exercise group (Figure 4.12). The auto-control group showed a significant decrease in the variation rate of insulin resistance yielded by the fasting insulin level and insulin concentration compared to the free exercise group (Figure 4.13). The auto-control group showed significant decreases in the blood variable index of hepatic metabolism—the variation rate of alanine transaminase in serum (ALT)—compared to the free exercise group and in the variation rate of γ-glutamyltrasferase (GGT) compared to the free exercise and self-control groups (Figures 4.14 and 4.15).

The auto-control group showed significant improvements in the blood variable components: the indices of lipometabolism, glycol metabolism, and hepatic metabolism. For the blood variable indices of lipometabolism, the total cholesterol and triglyceride in serum decreased significantly by 6.6% and 29.0% respectively; HDL cholesterol showed a significant increase of 7.1%. The ratio of total cholesterol/HDL cholesterol, which is a qualitative index of lipometabolism decreased significantly by 22.4% with the IFM system. For the blood variable indices of glycol metabolism, the fasting insulin level and blood concentration of insulin decreased significantly by 6.7% and 20.0%, respectively. HOMA-IR, which means the insulin resistance, decreased by 26%; HOMA-β, which is the index of the secretion capacity of insulin, and glycosylated hemoglobin molecule (HbA1c), which reflects the blood sugar over 2–3 months, did not show significant differences. For the blood variable indices of hepatic metabolism, ALT and GGT, which are indices of the liver function and metabolites, decreased significantly by 15.4% and 28.0%, respectively.

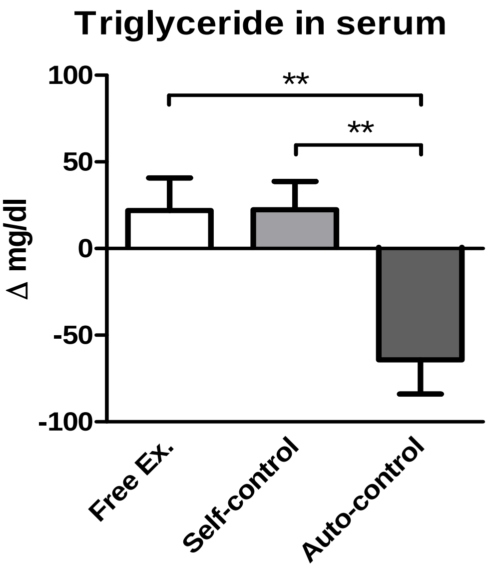


Figure 4.10 Variation rates of triglyceride in serum for each group. ** $p < 0.01$ compared with auto-control system group.

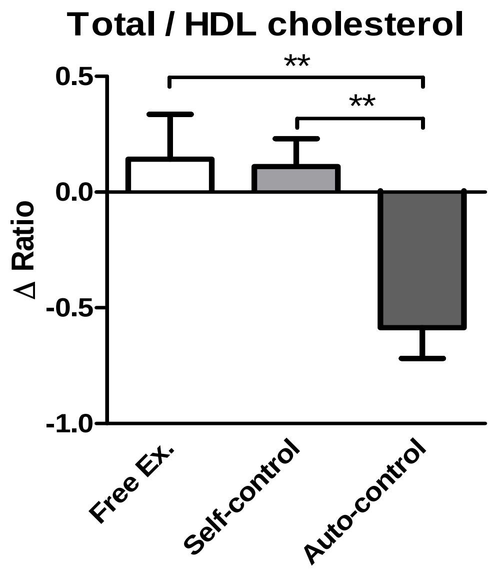


Figure 4.11 Variation rates of total/HDL cholesterol for each group. ** $p < 0.01$ compared with auto-control system group.

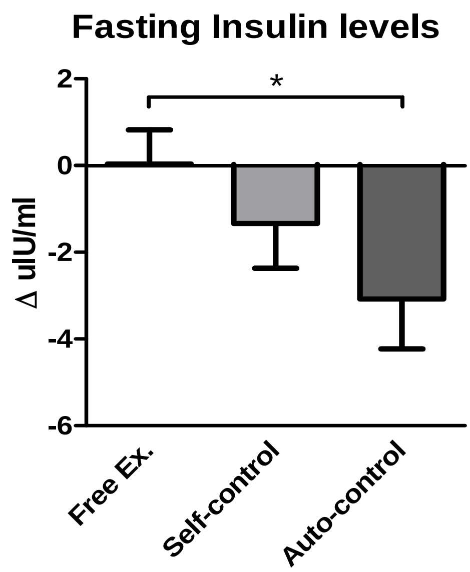


Figure 4.12 Variation rates of fasting insulin levels for each group. * $p < 0.05$ compared with auto-control system group.

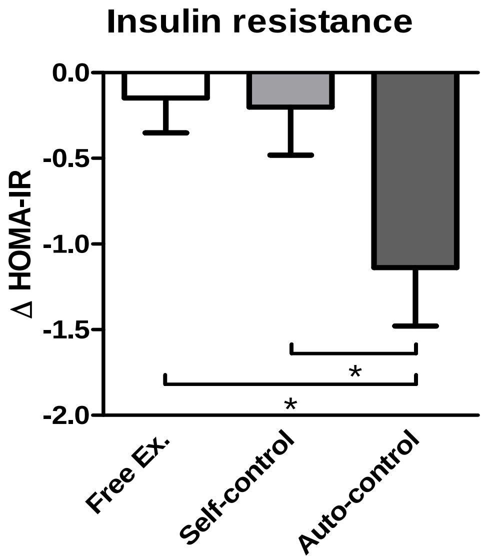


Figure 4.13 Variation rates of insulin resistance for each group. * $p < 0.05$ compared with auto-control system group.

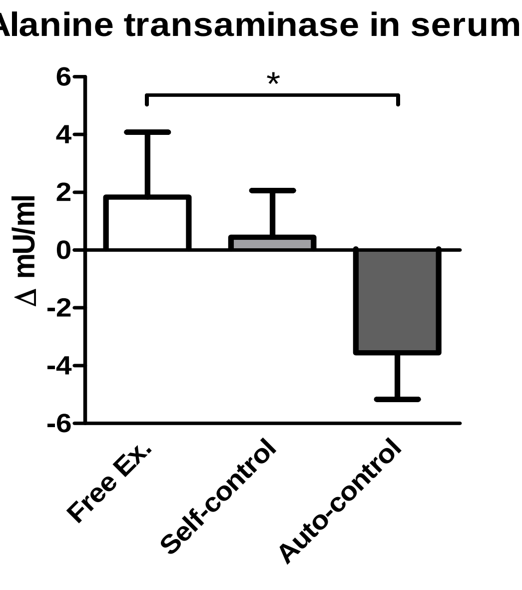


Figure 4.14 Variation rates of ALT for each group. * $p < 0.05$ compared with the auto-control system group.

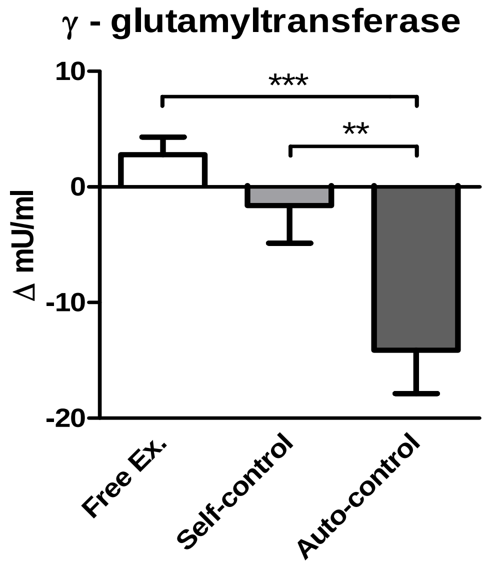


Figure 4.15 Variation rates of GGT for each group. ** $p < 0.01$, *** $p < 0.001$ compared with auto-control system group.

4.4.4 Variations in exercise variable components

A comparison of the exercise variable components confirmed that the auto-control group increased the variation rates of cardiopulmonary endurance, muscular endurance, and body flexibility more than the free exercise and self-control groups. The latter two groups showed no statistically significant differences.

The auto-control group was confirmed to significantly increase the variation rates of cardiopulmonary endurance, muscular endurance, and body flexibility as components of basal physical fitness, while the other groups showed no statistical significant differences for each exercise variables component.

Table 4.4 Exercise effect induced by free exercise

Variable	Before exercise training	After exercise training	Δ value	p value
Body composition				
Weight(kg)	75.5±12.1	74.6±12.8	-0.9	.058
Waist (cm)	94.4±6.8	92.0±8.9	-2.4	.107
BMI	28.2±4.1	28.0±4.4	-0.2	.129
Body fat (%)	31.7±5.4	31.4±5.9	-0.3	.472
Total Muscle mass (kg)	47.2±7.3	46.7±7.2	-0.5	.074
Skeletal muscle mass (kg)	24.0±5.3	24.0±4.7	-0.5	.663
Abdominal fat (%)	0.916±0.058	0.914±0.060	-0.002	.638
Visceral fat (kg)	3.50±1.17	3.25±1.36	-0.25	.117
Subcutaneous fat (kg)	20.5±5.7	20.2±6.3	-0.3	.169
Hemodynamics				
SBP (mmHg)	130.9±16.5	126.1±12.9	-4.8	.122
DBP (mmHg)	77.4±11.0	75.1±8.4	-2.3	.315
HRrest (beats/min)	66.7±8.5	65.6±7.7	-1.1	.754
SBP×HRrest (mmHg·beats/min)	8816±2043	8315±1546	-500	.396
Blood variables				
Total cholesterol (mg/dL)	207±77	204±30	-3.0	.267
Triglyceride (mg/dL)	133.1±64.3	154.9±70.6	21.8	.267
HDL-cholesterol (mg/dL)	49.7±12.7	50.4±9.2	0.7	.127
LDL-cholesterol (mg/dL)	132.0±75.7	134±29.2	2.1	.085
Fasting glucose (mg/dL)	112.8±65.0	103.4±48.4	-9.3	.149
Fasting insulin (μIU/ml)	8.04±5.10	8.08±4.44	0.04	.845
Insulin resistance (HOMA_IR)	2.15±1.42	2.00±1.11	-0.14	.486
Insulin secretion (HOMA_β)	87.72±60.11	106.8±94.9	19.1	.420
HbA1c (%)	6.08±1.18	5.85±0.35	-0.23	.323
AST (U/L)	25.9±6.0	23.8±5.8	-2.1	.097
ALT (U/L)	21.3±6.6	23.2±8.8	1.9	.586
GGT (U/L)	23.0±13.1	25.8±16.0	2.8	.141
Exercise variables				
VO2max(ml·kg−1·min−1)	30.1±6.7	30.0±6.8	-0.1	.619
Hand grip strength (kg)	34.4±8.6	35.0±7.4	0.6	.423
Sit-up (frequency/30sec)	12.2±5.3	15.1±5.1	2.9	.008
Sit-and-Reach (cm)	10.7±10.0	11.7±9.2	1.0	.478
Vertical jump (cm)	24.2±7.6	23.4±6.3	-0.8	.356
Reaction time (milliseconds)	338.6±90.0	322.4±86.8	-16.2	.570
Stork balance stand (seconds)	16.8±22.0	16.4±22.0	0.4	.660

Values are mean ± standard deviation. BMI: body mass index, SBP: Systolic blood pressure, DBP: Diastolic blood pressure, HRrest: resting heart rate, HbA1c: glycosylated hemoglobin, AST: aspartate transaminase, ALT: alanine transaminase GGT: ɤ - glutamyltransferase.

Table 4.5 Exercise effect induced by self-control exercise

Variable	Before exercise training	After exercise training	Δ value	p value
Body composition				
Weight(kg)	80.7±11.1	80.2±11.2	-0.4	0.93
Waist (cm)	98.6±6.9	96.4±6.4	-2.2	026
BMI	29.4±1.9	29.4±1.8	-0.03	.615
Body fat (%)	33.0±4.7	32.7±4.5	-0.3	.144
Total Muscle mass (kg)	49.8±9.4	49.7±9.4	-0.1	.754
Skeletal muscle mass (kg)	24.1±5.8	24.9±6.1	-0.7	.184
Abdominal fat (%)	0.914±0.051	0.918±0.058	0.007	.357
Visceral fat (kg)	3.89±0.72	3.83±0.74	0.06	.243
Subcutaneous fat (kg)	22.5±3.0	22.1±3.0	0.4	.023
Hemodynamics				
SBP (mmHg)	135.2±16.9	131.9±12.4	-3.3	.256
DBP (mmHg)	83.6±12.8	78.4±9.5	-5.2	.046
HRrest (beats/min)	72.3±9.9	70.4±10.5	-1.9	.170
SBP×HRrest (mmHg·beats/min)	9771±1826	9314±1698	-457	.170
Blood variables				
Total cholesterol (mg/dL)	194±23	201±28	6.7	.129
Triglyceride (mg/dL)	138±79	160±59	22.4	.035
HDL-cholesterol (mg/dL)	52.8±13.7	52.0±9.8	-0.8	.924
LDL-cholesterol (mg/dL)	113.3±19.2	147.4±28.2	34.1	.000
Fasting glucose (mg/dL)	97.2±15.9	98.2±18.1	1.0	.445
Fasting insulin (μlU/ml)	11.31±5.14	9.98±6.24	-1.33	.170
Insulin resistance (HOMA_IR)	2.67±1.14	2.46±1.67	-0.21	.267
Insulin secretion (HOMA_β)	139.6±81.0	112.4±72.9	-27.2	.048
HbA1c (%)	5.88±0.77	5.86±0.45	-0.02	.244
AST (U/L)	26.4±8.5	26.2±8.4	0.2	.856
ALT (U/L)	32.0±21.2	32.4±22.8	0.4	.760
GGT (U/L)	40.6±29.3	39.0±32.7	-1.6	.737
Exercise variables				
VO2max(ml·kg−1·min−1)	27.6±5.5	28.8±5.9	1.2	.184
Hand grip strength (kg)	35.2±9.5	35.3±8.9	0.1	.879
Sit-up (frequency/30sec)	14.3±6.9	14.9±6.7	0.6	.240
Sit-and-Reach (cm)	9.8±6.7	10.0±6.3	0.2	.616
Vertical jump (cm)	26.5±9.6	26.6±9.0	0.1	.585
Reaction time (milliseconds)	345.8±100.6	281.7±85.9	-64.1	.048
Stork balance stand (seconds)	23.1±26.5	25.4±26.4	2.33	.331

Values are mean ± standard deviation. BMI: body mass index, SBP: Systolic blood pressure, DBP: Diastolic blood pressure, HRrest: resting heart rate, HbA1c: glycosylated hemoglobin, AST: aspartate transaminase, ALT: alanine transaminase GGT: ɤ -glutamyltransferase.

Table 4.6　Exercise effect induced by auto-control exercise (IFM system)

Variable	Before exercise training	After exercise training	Δ value	p value
Body composition				
Weight(kg)	77.3±9.6	74.7±8.7	-2.7	.002
Waist (cm)	95.5±8.1	92.2±6.6	-3.3	.002
BMI	28.1±3.2	27.3±2.7	-0.8	.015
Body fat (%)	32.0±5.7	30.7±5.5	-1.3	<.001
Total Muscle mass (kg)	48.2±7.6	47.7±7.7	-0.6	.058
Skeletal muscle mass (kg)	23.7±5.7	24.6±6.0	0.9	.171
Abdominal fat (%)	0.908±0.061	0.896±0.061	-0.012	.002
Visceral fat (kg)	3.57±1.02	3.18±0.87	-0.38	<.001
Subcutaneous fat (kg)	21.2±4.7	19.6±3.9	-1.5	<.001
Hemodynamics				
SBP (mmHg)	131.1±19.2	120.6±14.4	-10.5	.018
DBP (mmHg)	79.2±2.7	73.5±2.1	-5.7	.048
HRrest (beats/min)	72.2±2.8	64.3±1.8	-7.9	.004
SBP×HRrest (mmHg·beats/min)	9394±2198	8451±1654	-1823	.002
Blood variables				
Total cholesterol (mg/dL)	198±50	182±41	-15.9	.011
Triglyceride (mg/dL)	176±148	112±79	-64.2	<.001
HDL-cholesterol (mg/dL)	49.8±13.6	52.9±14.2	3.1	.040
LDL-cholesterol (mg/dL)	121.9±33.6	124.7±43.0	2.8	.658
Fasting glucose (mg/dL)	102.2±24.2	92.5±11.8	-9.7	.021
Fasting insulin (μlU/ml)	9.97±5.88	6.89±3.99	-3.1	.036
Insulin resistance (HOMA_IR)	2.69±1.88	1.56±0.80	-1.13	.007
Insulin secretion (HOMA_β)	122.8±84.1	104.8±95.4	-7.99	.629
HbA1c (%)	5.93±0.68	5.88±0.36	-0.05	.886
AST (U/L)	26.0±7.4	25.2±8.5	-0.8	.378
ALT (U/L)	27.7±15.9	24.5±14.3	-3.6	.043
GGT (U/L)	38.7±29.6	24.6±15.1	-14.1	<.001
Exercise variables				
VO2max(ml·kg−1·min−1)	28.1±6.0	31.7±10.6	3.6	.020
Hand grip strength (kg)	34.8±9.8	35.2±10.1	0.4	.559
Sit-up (frequency/30sec)	10.5±6.7	14.3±6.6	3.7	.001
Sit-and-Reach (cm)	9.9±708	11.6±8.3	1.4	.033
Vertical jump (cm)	25.4±8.5	25.8±8.1	0.42	.392
Reaction time (milliseconds)	353.9±85.7	320.8±84.7	-33.1	.091
Stork balance stand (seconds)	20.0±22.1	20.1±24.1	0.05	.647

Values are mean ± standard deviation. BMI: body mass index, SBP: Systolic blood pressure, DBP: Diastolic blood pressure, HRrest: resting heart rate, HbA1c: glycosylated hemoglobin, AST: aspartate transaminase, ALT: alanine transaminase GGT: ɤ -glutamyltransferase.

Chapter 5

Discussion

5.1 Assessments of IFM system and experiments

The aims of this thesis were to design a personalized optimal exercise management system for reducing obesity and to verify its usefulness and superiority.

The proposed IFM system can automatically provide a personalized optimal exercise intensity based on exercise prescription theory to manage obesity and exercise information management based on an integrated database server. In particular, the novel automatic control system can provide a safer and more effective control method for the obese than existing optimal automatic exercise intensity control systems. Existing control methods have focused on optimal control to reach the target exercise intensity; however, they can provide rather immoderate exercise to the obese, who find it hard to easily adapt to drastic variations in exercise intensity, and can have a negative effect on the obese continuing to exercise.

In this thesis, individual perceived exercise intensity conditions are determined using RRI and RRI STD; these are then used to suggest an optimal control method based on a statistical model to control the target exercise intensity for the obese. The proposed IFM system provides the optimal effect and minimizes the variation in the perceived individual exercise intensity. The proposed statistical control model limits drastic variations in the initial exercise intensity through optimal transient response control and was designed to provide an appropriate personalized exercise intensity based on real-time individual bio-signal conditions to compensate for the weakness of existing PID-based controllers. The proposed IFM system is more effective at reducing obesity because it also provides guidance for resistance exercise, which is not considered in existing automatic control systems for fitness management.

To verify the proposed IFM system, an 8-week experiment was conducted with one experimental group using the IFM system and two control groups for comparison. The free exercise control group exercised on their own without any interference, and the self-control group were provided information on exercise and controlled their exercise intensity using a HR monitor. The experiment results were analyzed in terms of four aspects: body composition, hemodynamics, blood variables, and exercise variables. In general, the auto-control group that used the IFM system shows superior improvement compared to the control groups.

For body composition, weight, BMI, %body fat, visceral fat mass, and %abdominal fat of the auto-control group decreased significantly compared with the control groups. The significant changes in these parameters are important to both reducing obesity and improving the quality of life [16, 27, 29, 94-97] because body composition information is widely known to be a predictive factor in judging mortality caused by obesity [14, 98]. The systematic exercise method and individualized exercise intensity control provided the most ideal body-type improvement effect for the obese; these improvements in body composition were interpreted to directly affect improvements in other parameters.

For hemodynamics, HRrest and pressure rate product of the auto-control group decreased significantly compared with the control groups. The decrease in HRrest means an improvement in cardio-motility capacity, which helps decrease the prevalence of cardio-related disease. The pressure rate product is calculated by multiplying SBP and HRrest together; its significant decrease means that the IFM system reduces the exercise strain of subject. Thus, the IFM system inhibits drastic changes in HR and increases in SBP [99]. The physical strain caused by exercise plays a crucial role in how much exercise can be endured, so the above results mean that the proposed IFM system includes two contradictive advantages: a decrease in exercise strain and increase in obesity reduction.

For blood variables, the significant decrease in the ratio of total cholesterol/HDL cholesterol and triglyceride in serum means an improved lipometabolism function. The decrease in the ratio of total cholesterol/HDL cholesterol caused by the decrease in total cholesterol and increase in HDL cholesterol is directly related to the decrease in low-density lipoprotein (LDL) cholesterol, which may induce arteriosclerosis [54, 100-102]. In particular, the parameters of lipometabolism in the auto-control group showed a distinct decrease, whereas they increased in the control groups. This proves that the proposed system can contribute to strong improvement of the lipometabolism function. The significant decrease in the fasting insulin level and insulin resistance, which are related to glycol metabolism, means that the IFM system can be effective at preventing diabetic complications [103]. In particular, the insulin resistance has a practical effect on several organs (muscles, liver, adipocytes, and etc.) [104, 105]. Based on the results of this thesis, the decrease in insulin resistance from using the IFM system can mean a significant decrease in fat burning through a significant decrease in the representative fat masses for the body composition parameters. The significant decreases in ALT and GGT, which are indices of the hepatic metabolism function, show that the IFM system can be effective at recovering hepatic functions that are damaged by obesity [106-108].

The IFM system is more effective than the other control groups (in particular, the self-control group) because of the difference in the amount of exercise performed and exercise participation. Basically, exercise participation is an important criterion related to maximizing the exercise effect and reducing obesity. In terms of exercise methodology, the auto-control group consistently performed the given exercise according to the personalized target exercise intensity, whereas the self-control group found it difficult to perform the target exercise intensity because they had to control the exercise intensity on their own, even though they were provided information on determining an appropriate personalized exercise intensity. The appropriate HR range (±10 of target heart rate) provided by the HR monitor was wider than that of the IFM system, and most of the subjects in the self-control group performed their exercise at lower than the target exercise intensity while within the allowed range. The results of this thesis confirmed that the self-control group who were not provided systematic exercise management performed lower amounts of exercise despite being provided the exercise methodology. This result was reflected by the degree of improvement in bio-related parameters. These marginal improvements also affected the will and interest of the subjects to continue exercise; thus, they may have had a negative effect on the overall reduction in obesity. Figure 5.1 shows the exercise participation by each group: the experimental group using the IFM system generally maintained an exercise schedule of 3 days per week, while the other groups tended to exercise less over time. The self-control group exercised less than the free exercise group. Thus, failure to adapt to the given exercise and the lower degree of obesity reduction were assumed to affect exercise participation. In contrast, the IFM system provided both motivation to continue exercise and satisfaction by systematic obesity management; thus, the IFM system is more effective and reduces obesity more effectively than other exercise methods.

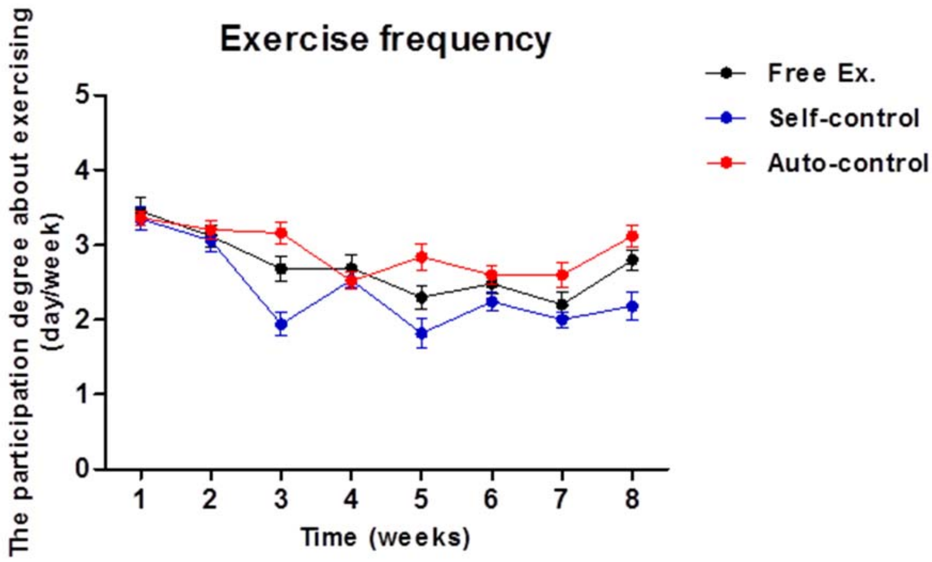


Figure 5.1 Participation degree in exercise.

5.2 Limitation of Thesis

The resistance exercise proposed in this thesis is not automatically controlled. If the resistance exercise is performed using hydraulic equipment, the strength of each step can be directly controlled by the automatic control system. However, hydraulic resistance exercise equipment currently available has limited applicability to personalized exercise management systems because they do not present the exact weight against hydraulic pressure. If this problem can be resolved, individual perceived exercise intensity monitoring based on muscle fatigue using hydraulic resistance exercise equipment will be feasible, and a complete personalized optimal exercise control system will eventually be developed.

Chapter 6

Conclusions

This thesis presented an intelligent fitness management (IFM) system based on personalized exercise guidance for obesity reduction. The novel system control model was designed for personalized optimal exercise intensity control based on bio-signal measurement and monitoring of the individual perceived exercise intensity condition. An obesity-customized aerobic and resistance exercise prescription method based on exercise prescription theory was proposed and then systemized for application to the IFM system. Exercise information and continuous exercise can be managed by connecting the IFM system to an integrated database server.

The experimental results obtained for the proposed IFM system confirmed a significant improvement in the body composition, hemodynamics, blood variables, and exercise variables compared to when other exercise methods (free exercise and self-control exercise by intervention) were used. The improved motivation to exercise was also confirmed through a survey of the participants.

The optimal exercise intensity for the obese and real-time control exercise intensity monitoring of the perceived exercise intensity by the IFM system helped reduce obesity more than the existing uniformed exercise intensity control method and robust control method, which are inappropriate for the obese. Based on these results, the proposed system can become a foundation for personalized exercise management to reduce obesity. If the proposed system can be introduced to the obese, it can help reduce obesity-related diseases and prevalence and thus improve the quality of life.

The proposed system includes an integrated database server; if personalized exercise prescriptions for other diseases can be integrated, the IFM system can be expanded to provide personalized exercise management services to the obese as well as those with other diseases.

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Appendix

A1. Certificate of approval of IRB for experiment

연세대학교 원주의과대학 연구윤리심의위원회

접 수 번 호	2011-28			접수일자	2011. 7. 30	
연구과제명	**바이오 피드백 기반의 토탈 운동 프로그램 효과**					
연구책임자	소 속	생리학교실	직 위	조교수	성 명	차승규
신 청 자	성 명	장 재 승		핸드폰	010-7118-2001	
				E-mail	skcha@yonsei.ac.kr	
연 구 기 간	승인 후 ~ 2011년 12 월 31 일					
연구의 종류	☐ 환자대상 설문조사 ☐ 일반인대상 설문조사 ☐ 정상세포배양 ☐ 보관된 검체연구 ☐ 의무기록을 이용한 연구 ☑ 조직 및 혈액연구 ☐ 관찰연구 ☐ 일반인 또는 환자를 대상으로 의학적 시술이 필요한 경우 ☑ 기타 (건강관련 체력 요인 검사 및 혈중지질 대사인자 변화 검사)					

위 연구책임자께서 제출하신 연구과제에 대하여 연구윤리심의위원회에서 검토하여 다음과 같이 결정하였음을 통지합니다.

- 다 음 -

심사일	2011. 8. 8	통보일	2011. 8. 15
심사결과	☑ 원안승인 ☐ 수정후 승인 ☐ 불승인		
평가 의견 및 수정 보완해야 할 사항			
수정 계획서 제출필요 여부	☐ 예 ☐ 아니오	제출기한	년 월 일

연세대학교 원주의과대학 연구윤리심의위원장

Abstract (in Korean)

비만을 위한 개인맞춤형 운동 가이드 기반의 지능형 건강관리 시스템 설계 및 적용

본 연구에서는 효율적이고 직접적인 비만 개선을 위한 개인맞춤형 운동 가이드 기반의 지능형 건강관리 시스템을 제안하고, 이 시스템을 검증하기 위하여 기존 운동 방법들과의 비교를 통해 비만관련 인자들의 개선 정도를 평가하였다.

비만은 심혈관계 질환뿐만 아니라 각종 대사관련 질환을 야기하며 고혈압, 당뇨 등의 합병증을 야기할 수 있기 때문에, 비만에 대한 관리와 치료는 매우 중요하다. 비만은 신체 활동과 밀접한 연관성이 있으며, 운동을 통한 신체 활동량의 증가는 비만 개선에 매우 효율적이다. 비만 개선을 위한 운동은 유산소 운동과 근력 운동을 함께 하는 것이 더 효율적이며, 같은 운동 강도에 대하여 정상인에 비해 상대적으로 더 큰 강도로 자각하는 비만인을 고려한 최적 운동 강도 제어 기술이 필요하다. 뿐만 아니라, 이러한 운동 방법은 운동에 대한 흥미를 유발시키고 지속적인 참여를 고취시킬 수 있는 체계적인 운동관리 시스템과 결합되어야 한다. 따라서, 본 연구에서는 체계적인 운동관리와 비만 개선을 위한 통

합 데이터베이스 기반의 지능형 건강관리 시스템을 설계하였으며, 비만인의 운동 강도 인지 상태를 반영하는 심전도의 R-R interval과 R-R interval의 표준편차를 이용한 통계적 모델과 이를 적용하는 바이오피드백 기반의 자동 제어 시스템을 제안하였다.

본 연구에서 제안한 지능형 건강관리 시스템은 비만 개선을 위하여 유산소 운동과 근력 운동을 결합한 체계적인 운동처방을 제공할 수 있을 뿐만 아니라 지속적인 신체 및 운동 정보를 관리함으로써 운동에 대한 흥미와 참여를 높이는데 기여하였다. 이 시스템에 내장된 비만인에게 최적화된 운동 강도 자동 제어 시스템은 기존 시스템에 비해 비만인에게 보다 안정적이고 효율적인 운동 방법을 제공함으로써 직접적인 비만 개선 효과를 얻을 수 있었다. 본 연구에서 제안한 지능형 건강관리 시스템을 검증하기 위하여, free-exercise group과 polar 장비를 이용한 self-control group를 대조군으로 지정하고 8주간 운동을 통하여 변화하는 신체조성, 혈액동태학, 혈액변인, 그리고 운동변인의 전후를 비교 분석하였다.

본 연구의 결과, 본 연구에서 제안한 시스템을 이용한 auto-control group이 다른 group에 비하여 월등한 개선 효과를 보였다. 신체조성에서는 몸무게, BMI, 체지방율, 복부지방율, 그리고 피하지방율에서 유의한 감소가 있었으며, 혈액동태학적인 요소들에서는 안정 시 심박수와 심부담도의 유의한 감소를 확인할 수 있었다. 혈액변인에서는 지방대사 (총 콜레스테롤/고밀도 지단백 콜레스테롤), 당대사 (공복 시 인슐린, 인슐린 저항성), 그리고 간대사 (Alanine transaminase, γ-glutamyltransferase)의 상태를 확인할 수 있는 호르몬과 효소들의 유의한 감소를 확인할 수 있었다. 마지막으로 운동변인에서는 건강관련 체력요소들인 심폐지구

력과 근지구력, 유연성에서 기능이 향상됨을 확인할 수 있었으며, 본 연구에서 제안한 시스템이 다른 운동 방법에 비해 높고 지속적인 참여를 고취시킬 수 있음을 확인하였다.

본 연구의 결과를 통해, 제안한 지능형 건강관리 시스템이 비만 개선을 위한 개인맞춤형 최적 운동처방을 제공해 줄 수 있으며, 지속적인 효과를 위한 운동 참여 유도에도 기여함을 알 수 있었다. 이 시스템이 비만 관리 센터나 피트니스 클럽에 적용이 된다면, 현재 심각하게 증가하고 있는 비만관련 질환과 비만 유병율을 감소시키는데 도움을 줄 수 있을 것이라 사료된다.

Key words: 비만, 자동제어, 통합 건강관리 시스템, 통계적 제어 모델, 신체조성, 혈액동태학, 혈액변인, 운동변인, 운동 참여도