Bayesian Networks-Based Interval Training Guidance System for Cancer Rehabilitation

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Abstract— **The number of cancer patients who live more than 5 years after surgery exceeds 53.9% over the period of 1974 and 1990; Treatments for cancer patients are important during the recovery period, as physical pain and cancer fatigue affect cancer patients' psychological and social functions. Researchers have shown that interval training improves the physical performance in terms of fatigue level, cardiovascular build-up, and hemoglobin concentration, the feelings of control, independence, self-esteem, and social relationship during cancer rehabilitation and chemotherapy periods. The lack of proper individual motivation levels and the difficulty in following given interval training protocols results in patients stopping interval training sessions before reaching proper exhaustion levels.**

In this work, we use behavioral cueing using music and performance feedback, combined with a social network interface, to provide motivation during interval training exercise sessions. We have developed an application program on the popular lightweight iPhone platform, embedded with several leveraged sensors. By measuring the exercise accuracy of the user through sensor readings, specifically accelerometers embedded in the iPhone, we are able to play suitable songs to match the user's workout plan. A hybrid of a content-based, context-aware, and collaborative filtering methods using Bayesian networks incorporates the user's music preferences and the exercise speed that will enhance performance. Additionally, exercise information such as the amount of calorie burned, exercise time, and the exercise accuracy, etc. are sent to the user's social network group by analyzing contents of the web database and contact lists in the user's iPhone.

Keywords-component; exercise guidance system, interval training, music recommendation, social networks, rehabilitation

I. INTRODUCTION

In a survery of cancer patients over 1974 and 1990, over 53.9% of the cancer patients survive more than 5 years after surgeries. As these patients have a chronic illness, treatments that relieve physical pain, fatigue, psychological and social problems are complex and comprehensive. Lehmann et al. [1] identified the needs of cancer population and concluded that 438 of 805 patients surveyed had impairments and functional limitations such as psychological distress, general weakness, work-related problems, finance, housing, family support, and dependence in activities of daily life after cancer surgeries. Among those factors, physical performance and lean mass are among the most important clinical factors to predict the survival rates of cancer patients. Factors related to cardiovascular and musculoskeletal models may advance the understanding of the adaptation in cancer patients. Hence, measures of aerobic fitness and daily activity are useful to measure and determine the patients' needs and their progress in rehabilitation efforts (Gerber [2]).

For cancer patients, cancer fatigue resulting from muscle weakness, pain or sleep disruption is seen most frequently and it causes distruptions in physical, emotional, and social functions. Since emotional and social functions are highly related to physical health status, improving physical performance and recovery is significant in aiding patients regain physical, mental and social health.

Many researchers and physicians recommend interval training to improve aerobic capacity, and to restore physical functions, and cardiovascular systems. Dimeo et al. [4] showed that among the group participating in interval training exercise, fatigue and somatic complaints did not increase and psychological distress such as obsession, fear, interpersonal sensitivity, and phobic anxiety were diminished. Interval training consists of interleaving high intensity exercises with rest periods. The high intensity activity is followed by low intensity activity, referred to as the recovery period. The improvement in physical performance such as fatigue level, maximum performance, cardiovascular build-up, and hemoglobin concentration (Dimeo et al. [3]) enhanced by interval training can increase the feelings of control, independence, self-esteem, and result in better social relationships with others. In addition, interval training is a well known exercise protocol which helps strengthen and improve one's cardiovascular system ([5] – [11]). Moreover, it has been shown to help with weight loss, general fitness, and the reduction of heart and pulmonary diseases, as compared with other continuous exercise methods. During interval training, the body's energy production system is utilized, and both aerobic and anaerobic energy sources are activated. Energy from these two sources is then efficiently distributed throughout the body for the duration of the workout period.

Despite interval training's health benefits, properly following given interval training protocols is not simple. Dimeo et al. [3] assumed that less motivated patients would stop the interval training session before reaching a certain proper exhaustion level.

To provide motivation and guidance in interval training exercise sessions, we present our behavioral cueing system developed for the popular iPhone platform. It uses music, sensor readings, and social networking to encourage and motivate users to follow a healthy exercise plan. As iPhones are very light, small and embedded with sensors, they can serve as a cheaper, a more convenient, and a multi-purpose alternative to traditional exercise equipment.

When recommending music to the user, our system uses three different filtering methods: content-based, context-aware, and collaborative filtering. Especially for collaborative filtering, Bayesian networks are applied to the system to select the appropriate music, based on music preferences of others and a probabilistic model. Additionally, competitive group exercise methods incorporated into the system may motivate users to participate in interval training type exercises. By using social networks, such as sending emails to friends and uploading rankings on a shared website, etc., users can be effectively motivated to continue interval training for their rehabilitation.

II. INTERVAL TRAINING MOTIVATIONS

A. *Music Motivation*

Terry et al. [12], Karageorghis et al. [13], and Mohammadzadeh et al. [14] examine how the rhythm of music related to personal factors and situational factors promotes more exercise with less stress. Athletes respond to the rhythmical qualities of music by synchronizing movement patterns to tempo. Rhythm related to the user's preference and situational conditions affect exercise and stress level. Works in time to music increases the likelihood of harder exercise for longer periods of time in a broad range of level of fitness. Listening to music provides benefits such as improvement in mood, pre-event activation or relaxation, dissociation from unpleasant feelings such as pain and fatigue, reduced rating of perceived exertion (RPE), especially during aerobic training. The exercise output can be extended through synchronization of music with movement, it can be enhanced when rhythm or association is matched with required movement patterns, and the music increases likelihood of athletes achieving flow states. Thus, music can be a good source of motivation during interval training, especially when the exercise method is tedious and repetitious.

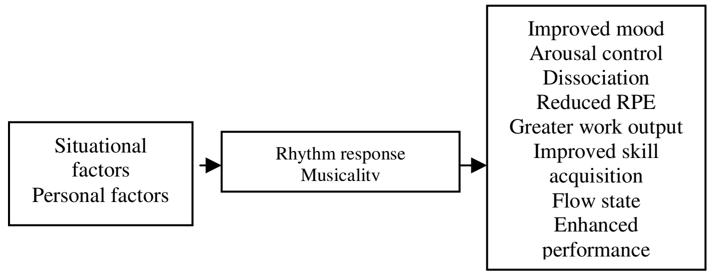

Fig 2.1. Benefits of listening to music in sports and exercise contexts.

B. *Competitive Group Exercise*

Competitive group interval training is another form of user motivation, with known beneficial effects on physiological functions. The experimental results (Kilpatrick et al. [15], Table 2.2, and Table 2.3) indicate that sport participants are more motivated to engage in physical activity as a means for enjoyment and to achieve positive health benefits. Sport participation is strongly related to affiliation, competition, enjoyment, and challenge. In addition, a program of aerobic, and endurance activities such as interval training, undertaken in a group setting, stimulates and improves physiological and cognitive functions and subject wellbeing (Williams et al. [16]). Since doing exercise together can help people maintain affiliation with friends and promote to exercise more, the designed system relates to social networks.

Subscale	Sample item
Affiliation	**To spend time with friends**
Appearance	To look more attractive
Challenge	**To give me goals to work toward**
Competition	**Because I like trying to win in physical**
Enjoyment	**Because I enjoy the feeling of exerting myself**
Health pressures	Because my doctor advised me to exercise
Ill-health avoidance	To prevent health problems
Nimbleness	To stay/become more agile
Positive health	To have a healthy body
Revitalization	Because it makes me feel good
Social recognition	**To show my worth to others**
Strength and endurance	To increase my endurance
Stress management	Because it helps reduce tension
Weight management	To stay slim

Fig 2.2 Several exercise motives

Subscale	Men	Women	Total
Affiliation	**4**	**1**	**2**
Appearance	11	12	12
Challenge	**3**	**3**	**4**
Competition	**1**	**4**	**1**
Enjoyment	**2**	**2**	**3**
Health pressures	14	14	14
Ill-health avoidance	13	13	13
Nimbleness	7	10	8
Positive health	8	7	7
Revitalization	6	5	5
Social recognition	**9**	**11**	**9**
Strength and endurance	4	6	6
Stress management	10	9	10
Weight management	12	8	11

Fig 2.3 Ranking of exercise motivation:

Range = 1 (most important) to 14 (least important)

C. *Light Weight Wireless Smartphone*

Without fitness equipment such as a treadmill, interval training is very difficult to follow, since individuals are unable to accurately determine or guess their current exercise intensity. On the other hand, traditional fitness equipment has significant space and cost restrictions. Therefore, the use of an inexpensive mobile handheld device can be an effective means for guiding interval training exercises. Ease of use, compatibility, and communicability are key issues related to mobile device use and adoption by individuals (Kleijnen [18]).

Sarker [17] mentions factors influencing the use of mobile handheld device by individuals, including technology, communication/task characteristics, modalities of mobility, and context (Fig 2.4.). Those same features support our choice of a smart phone platform for our system.

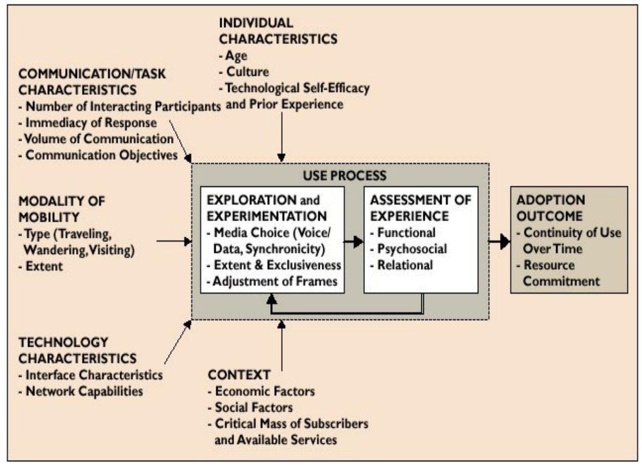

Fig 2.4. Factors influencing mobile handheld device use and adoption [17]

Accelerometers are currently among the most widely studied wearable sensors for activity recognition. They are also very useful for interval training. By analyzing data obtained from three different axes, the accuracy of exercise and the caloric consumption can be calculated. This information can be used to calculate one's score to motivate the user to compete with other peoples in order to obtain better score. Accelerometers are commonly embedded in smart phones, such as Apple iPhone, Google G1, and Nokia N95. Moreover, smart phones can help individuals to follow scheduled speeds, during a specific time period, and can also give feedback using the cell phone's sound, vibration, and other graphical interfaces. Additionally, their calculation functionalities can also be leveraged.

With technology, the easy interface of a mobile device is important. An iPhone's 3.5 inch multi-touch display with 480-by-320-pixel resolution makes users navigate by touching the screen. The multi-touch display layers a protective shield over a capacitive panel that senses touches using electrical fields. It then transmits that information to the LCD screen below it, and the iPhone software enables the flick, tap, and pinch. The iPhone display also supports multiple languages and characters for users worldwide.

Poor network characteristics act as severe inhibitors to use and adoption. For example, the lack of coverage in many areas tend to reduce the sense of freedom and safety in many subject's minds. The iPhone 3G uses a technology protocol called HSDPA (High-Speed Downlink Packet Access) to download data quickly over UMTS (Universal Mobile Telecommunications System) networks. Accessing the internet to load information is twice as fast on 3G networks as on 2G EDGE networks. Since the iPhone 3G meets worldwide standards for cellular communications, a user can make calls and surf the web from practically almost anywhere. When a user is not in a 3G network area, the iPhone uses a GSM network for calls and an EDGE network for data.

Fig 2.5. The size and weight of an iPhone

According to the market research group NPD, Apple's iPhone 3G topped the sales charts in the third quarter of 2008. Therefore, many iPhone users and developers share information regarding iPhone systems and applications via several websites or magazines. In addition, the number of interactions among iPhone user groups and developer groups continues to increase.

Research has shown that, for a variety of reasons, humans are attracted to the natural environment (Knoph [18], [19], and Kaplan [20]). These investigations have shown that when encountering or presented with images of natural environments, subjects experience a variety of positive psychological, social, and physiological outcomes. Since an iPhone weighs only 133g, it is easy to carry outdoors where interval training can be performed; the only limitation is the possession of a light 3G smart phone.. In a gym, on the other hand, a person is limited to a treadmill

Sarker [17] also emphasizes on the modalities of mobility for the use of adoption in mobile devices. Traveling, wandering, and visiting are seen as three ways to qualifying the essence of mobility (Kristoffersen [21]). Traveling is defined as the process of going from one place to another in a vehicle. Wandering refers to an extensive local mobility where an individual may spend considerable time walking around. Visiting refers to stopping at some location and spending time there, before moving to another. Three different types of mobilities are associated with different motivations of a user. For instance, safety is an important concern for a person traveling frequently. Therefore, the iPhone's 3G internet connectivity, and light size can be a good source of motivation to use in this system for all three different groups.

III. SYSTEM DESIGN

In our system, we use the iPhone [22] and a web server system for our development. The iPhone is a 133g, 3.5 inch multi-touch display smart phone that supports both Wi-Fi and Bluetooth. Furthermore, the iPhone has an in-built accelerometer, a light and a proximity sensor. By using an embedded 3-axis accelerometer on the iPhone, activity patterns are detected. QuickTime, a proprietary digital media player application, is embedded in the iPhone, and it is capable of handling various formats of digital video, media clips, sound, text, animation, music, and interactive panoramic images. Also, the iPhone features the Safari web browser with 3G and Wi-Fi, which allows the user to access the Internet almost anywhere. When songs and users' information are stored on a web server, the 8 or 16 gigabytes storage of an iPhone doesn't have to be wasted. The remaining data storage can be used for other purposes. Based on given information, the system recommends suitable songs, and connects users.

A. Music Recommendation

As mentioned, music is a good source of motivation during exercise by synchronizing movement patterns to the rhythm of the music. In addition, personal factors such as one's age, sex, cultural background, and education level also affect one's taste in music. Therefore, the group of users who share similarity can be generated by collaborative filtering technique. A user's choice in music in the past can affect the list of recommended music by content-based filtering. Content-based recommendation systems with collaborative filtering analyze the content of the objects that a user has preferred in the past, and they recommend other relevant contents by using one's history and the nearest neighbor's information (Park [23], Adomavicius [27], Balabanović [28]).

Based on training data, a user model is induced that enables the content-based filtering technique to classify unseen items. The training set consists of the items that the user has found interesting. These items form training instances that all have an attribute. This attribute specifies the class of the item based on either the rating of the user or on implicit evidence. With the class information, the list of recommended items is determined. A content-based filtering system selects items based on the correlation between the content of the items and the user's preferences, as opposed to a collaborative filtering system that chooses items based on the correlation among people with similar preferences. Collaborative filtering is the process of filtering for information or patterns using techniques involving collaboration among multiple agents who share similarities in attributes. The LIBRA system

(Mooney [29]) recommends books by using content-based and collaborative filtering. Many systems use hybrid features of content-based and collaborative filtering to recommend items. Those systems combine knowledge about users who liked a set of items with knowledge of a particular content feature associated with the item in one user's set.

User context is any information that can be used to characterize the situation of an entity. Context includes location of use, the collection of nearby people and objects, accessible devices, and changes to these objects, etc. A context-aware system in recommendation systems is to provide a user with relevant information and services based on one's current context (Van Setten [25]). Context information which characterizes the situation of the user, place or objects should be considered to recommend proper music to the user. For example, Van Setten [25] realizes the mobile tourist application which takes account the user's interests and contextual factors such as the place last time visited. The PILGRIM recommendation system (Brunato [26]) uses mobility-aware filtering techniques with a GPS system. Our system recognizes the exercise context by using user input such as exercise time, the amount of calorie to be burned and data stream from an accelerometer. Using this information, the system can recommend suitable music for the exercise context.

Our system classifies songs by genre and the speed of the music, and it recommends the songs to the user based on the user's history and background. The system classifies users based on age, gender, and residential location. Recommendations for users are in the same group are affected by the annotations of other members of the group. In addition, music which corresponds to the speed and the intensity of interval training is recommended to the user. A 3-axis accelerometer embedded in the iPhone and user input are used to select a suitable music. The system filters music recommendations using a comparison or target speed and current speed. For instance, when the user runs slower than the target speed, faster music is played. Therefore, our system realizes the collaborative, content-based, and context-aware recommendation by analyzing the user's information, the group the user belongs to, and the speed of the exercise. As user's annotation is accumulated in the database, the list of the recommended music is also updated and made more suitable for the user and the exercise context. Thus the recommended music is modified and adapted, as the number of annotation data increases.

The music database currently stores 822 mp3 files, which is around 4.64 gigabytes. Since songs are not stored on the iPhone, the remaining storage can be used for other purposes.

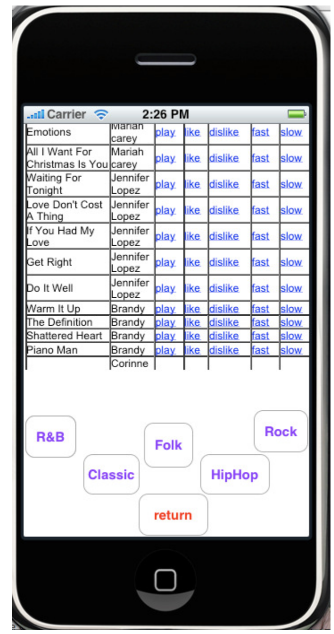

Fig 3.1. An example of the music recommendation part in our system

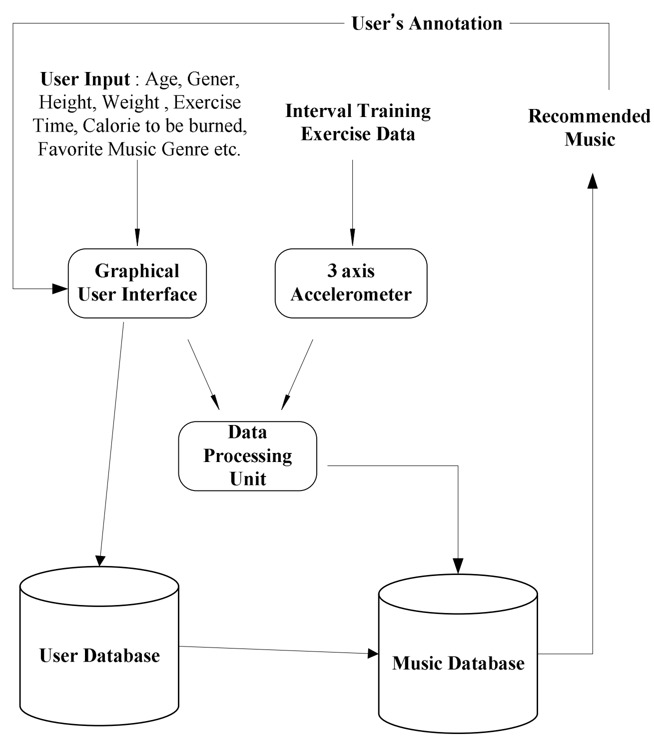

Fig 3.2. The structure of context-aware, content-based, and collaborative music recommendation system

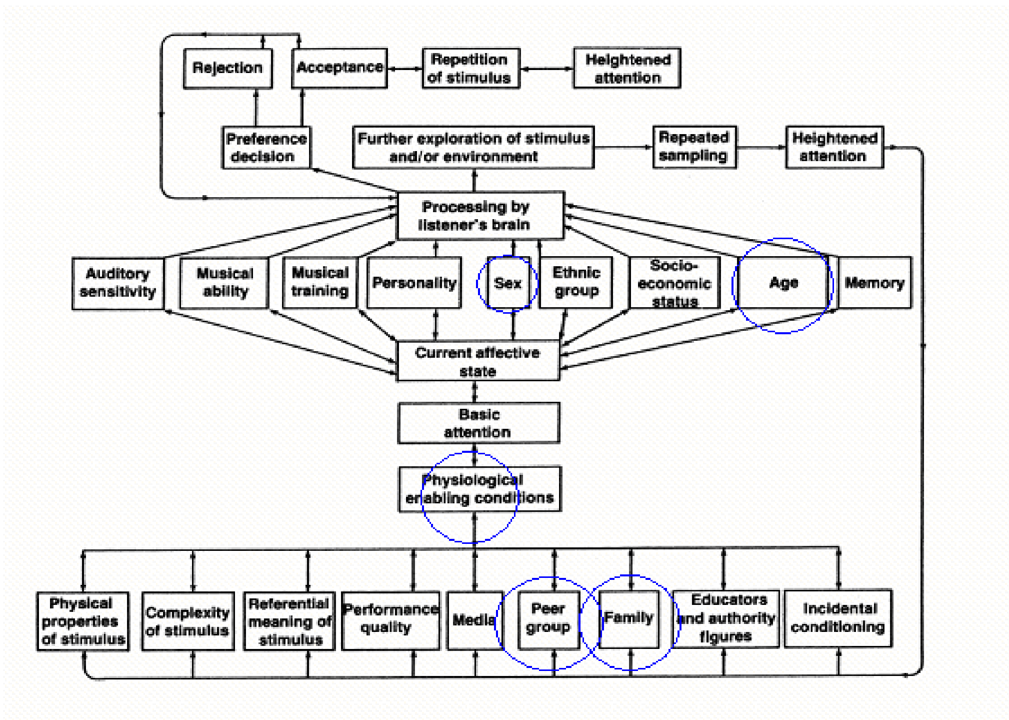

Fig 3.3. Sources of variation in music preference

The preference of music can be determined by a listener's age, gender, ethnic group, residential area, family and peer group, etc. LeBlanc ([30], [31]) examines that the age of a music listener exerts a strong influence on overall preferences of music style and the speed of music. Christenson [32] denotes gender is central to the ways in which popular music is used and tastes are organized. Even though the underlying structure of music preference cannot be accounted for by reference to two or three factors, there are crucial difference between males and females in terms of their mapping of music types. In addition, preferences in popular music also vary according to the neighborhood in which the music listener lives (Johnstone [33]). People can also be affected by their family and peer groups, or their backgrounds, such as music training experience and level of education. There are additional factors which affect the music preference shown in Fig 3.3.

Using the structure in Fig 3.3. and information which can be obtained by iPhone such as sex, age, and exercise intensity, location data obtained by GPS embedded in the iPhone, etc. , a Bayesian network structure in Fig 3.5. is designed. Peer group is assumed to be formed by age, gender, and residential district, since these factors affect perceptions of relationships (Furman [34]). Physiological enabling condition is assumed to be related to the exercise intensity information such as exercise time, and calories to be burned in the user's input.

Based on the above assumptions, a Bayesian network model is obtained and is used to calculate the probability that the given song is recommended by people sharing similarities with the user. Bayesian networks are a probabilistic model using a set of random variables and conditional relations. This probabilistic model attempts to make valid predictions based on only a sample of all possible observations.

$$\Pr(CityA, Age5-10, Speed0-5, Male \mid SelectMusicA) =$$

$$\frac{\Pr(CityA) * \Pr(Age5-10 \mid CityA) * \Pr(Speed0-5 \mid Age5-10) * \Pr(Male \mid Speed0-5) * \Pr(SelectMusicA \mid Male)}{\Pr(SelectMusicA)}$$

$$\geq \text{Threshold}$$

Fig 3.5. Probabilistic model of Fig 3.4.

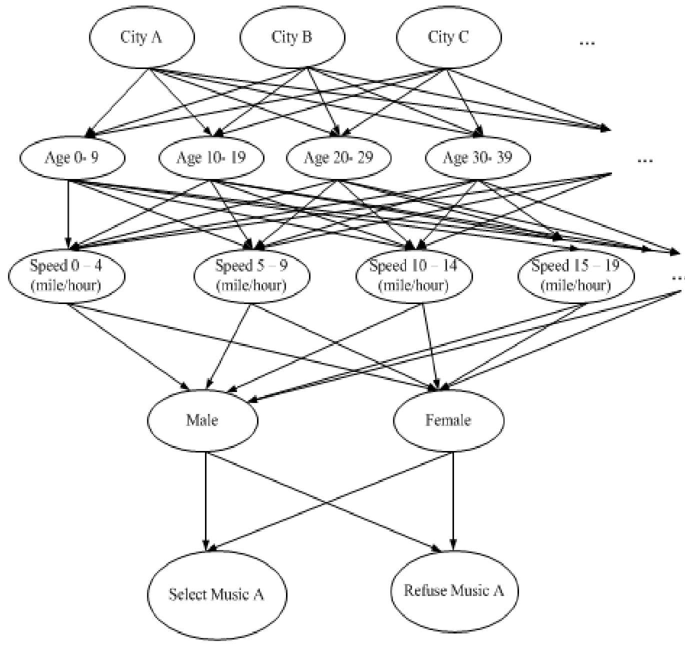

Fig 3.5. Bayesian networks related to music preference and choice

B. *Interval Training Game with Social Network*

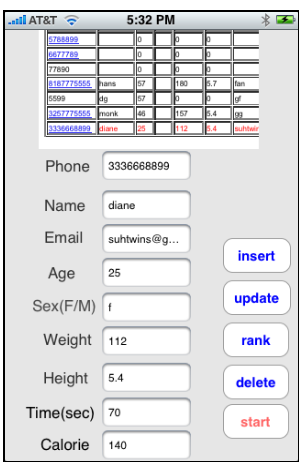

Fig 3.5. User input screen

With the inserted user input (Fig 3.5), the system design is customized to an interval training protocol. The user input screen requires user information including weight, height, the amount of time to exercise, and the amount of calorie to be burned. By using the following equation, the system designs a customized exercise plan for the user.

$$W = m \cdot g \cdot h \cdot h\_rate \cdot v' \cdot t + \frac{1}{2} \cdot m \cdot v^2 \cdot t \text{ (J)}$$

m: mass (kg)

g : the gravitational constant (kg/m2)

v : the speed of running (m/s)

v' : the number of steps per second (steps/s)

t : collapsed time (s)

h : height (m)

h_rate : the rate of height lifted up when walking/running

An iPhone provides a 3.5 inch 480-by-320-pixel resolution multi-touch display, an audio system which has a frequency rate from 20Hz to 20,000Hz, and vibration functionality. Our system gives three different feedback commands to the user through the use of sound, vibration and animation based on the developed schedule.

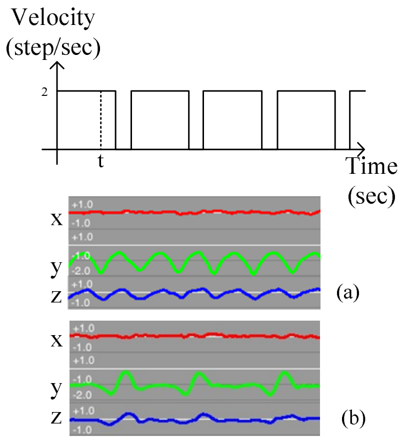

Fig 3.7. Scheduled interval training and the accelerometer data for the accurate exercise (a) and the inaccurate exercise (b) at time t

By comparing the determined schedule of the interval training exercise with the exercise data collected via a 3-axis accelerometer embedded in an iPhone, the accuracy of the exercise is calculated. The system gives a lower score to the user who does not complete the interval training session accurately in order to motivate the user to exercise more and more precisely in an effort to get a better score. For instance, the accuracy of the exercise shown in Fig 3.7. is 50%, since only 3 steps among 6 given commands are completed.

$$\text{Accuracy} = \frac{\text{The number of correct steps}}{\text{The number of times commands are given}}$$

The user's interactions with the iPhone are synchronized with the user's online profile registered in the web database of our system and the user's friend group, a group of users who participate in the iPhone interval training guidance system. E-mails containing the accuracy of the exercise sessions, exercise session time, and the amount of calories burned, etc. can be sent to other members in the user's social networking group after an exercise session is completed in order to increase the interaction among the user's friend group and to use the sharing of the information to increase the motivation to exercise, in the hopes of competing with friends.

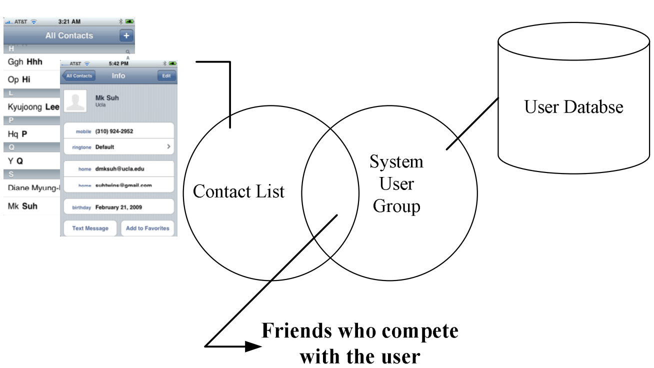

Fig 3.8. The method to get the friend group who compete with the user in our system

IV. Experimental Results

A. *The Effect of Interval Training Guidance Systems*

As shown in Table 4.1, eight different individuals participated in the experiment to test the effectiveness of our system. All of these individuals are between the ages of 20 and 30, and they all live in Los Angeles, California. Exactly half of the participants are female.

	Individual 1	Individual 2	Individual 3	Individual 4	Individual 5	Individual 6	Individual 7	Individual 8
Gender	**Female**	**Male**	**Male**	**Female**	**Female**	**Male**	**Male**	**Female**
Age	**25**	**24**	**27**	**28**	**25**	**29**	**27**	**25**
Weight (kg)	**51**	**61.4**	**73**	**49.5**	**50.5**	**62**	**70**	**51**
Height (cm)	**158**	**170**	**175**	**163**	**164**	**172**	**175**	**158**
Residential District	**Los Angeles, CA**	**Los Angeles, CA**	**Los Angeles, CA**	**Los Angeles, CA**	**Los Angeles, CA**	**Los Angeles, CA**	**Los Angeles, CA**	**Los Angeles, CA**

Table 4.1. Information about individuals who participated in the experiment

Compared with uncontrolled condition, the experiment (Fig 4.2.) shows that exercise commands generally help users to exercise more accurately. Especially for individual 4, the accuracy of the exercise was improved from 53.97% to 88.71%. Dimeo [3] showed, 7 weeks after discharge, improvement of maximum performance, cardiovascular system build-up, fatigue level, and hemoglobin concentration is significantly increased in the interval training exercise group.

It shows that the most effective command combination is different from each person. Hale [35] also mentions different people have different time to perform information processing task depending on the type of information. This result also can be affected by the circumstance of the experiment. For example, the sound command is not a proper exercise command to the user in the noisy area or for the user who has a hearing problem.

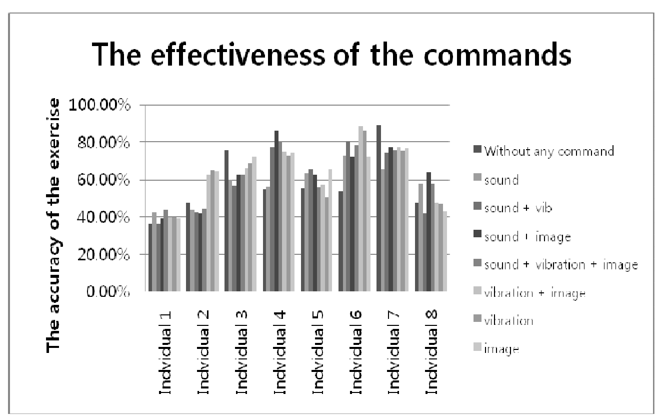

Fig 4.2. The accuracy of the exercise with given commands.

Since the vibration affects the reading of the 3-axis accelerometer data, it has more than 85 % of the false positive rate(Fig 4.3). When using probabilistic model(Fig 4.4) to calculated true positive rate of the movement detection with using vibration commands, the true positive detection rate of indvidual 5 is 0.44.

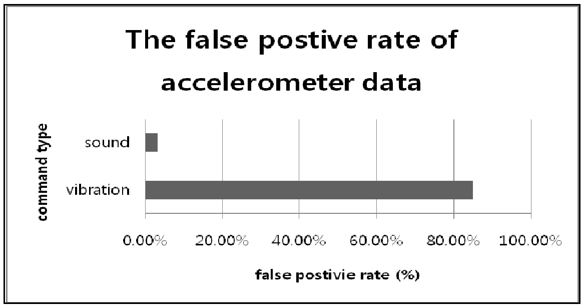

Fig 4.3 The false positive rate of accelerometer data with and without vibration command

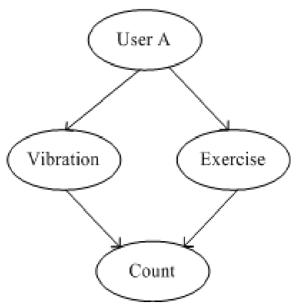

Fig 4.4. Probabilistic model to calculate true positive rates using vibration commad

B. *A Music Recommendation System Suitable for Interval Training Exercise*

Each individual, as shown in Fig 4.2., was requested to annotate his/her preference in music by using the music annotation user interface. Members in each individual group share gender, age, and residential area. Each song in the web database was annotated more than 8 times. Fig 4.5 shows the number of refused songs among 10 recommendations for a 30 years old, 180cm, and 80kg individual living in Los Angeles, California. Compared with the method which recommends music preferred by people who share the same age range, gender, similar exercise intensity and residential area, Bayesian networks-based recommendation method is better for selecting suitable exercise music.

In addition, by using content-based filtering, if there is music that only one specific individual does not like, this song will not be recommended for that user, but still will be recommended to others until the rating is below the threshold level. Music is also selected by the intensity of the interval training. The appropriateness of music in the exercise context is more suitable than in the uncontrolled condition using random music. This content-based, context-aware, and collaborative music recommendation system will choose suitable music for the user who is engaged in the interval training.

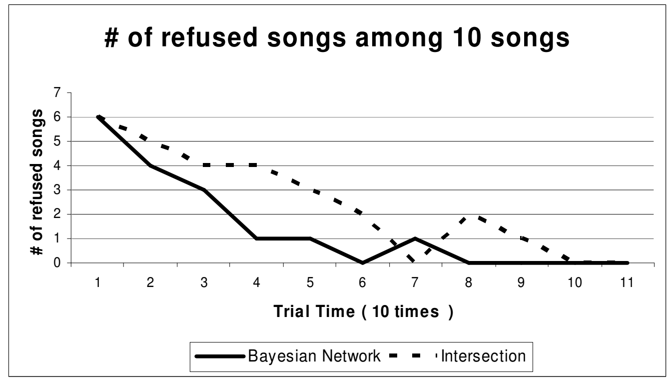

Fig 4.5. The number of refused music among 10 recommended

V. CONCLUSION

Interval training involves a series of intensive exercises to provide proper stress to cardiovascular and musculoskeletal systems with recovery periods. Interval training exercises include establishing a period for high intensity activity, followed by a period of low intensity activity referred to as a recovery period, a frequency with which this cycle is repeated, and finally a number of cycles corresponding to one complete session after which the subject ceases activity. Interval training improves the physical performance in terms of fatigue level, cardiovascular build-up, and hemoglobin concentration, the feelings of control, independence, self-esteem, social relationship during cancer rehabilitation and chemotherapy periods. Furthermore, interval training is beneficial for weight loss, rehabilitation, general health, and cardiovascular build up. However, the lack of proper individual motivation levels and the difficulty in following given interval training protocols results in patients stopping interval training sessions before reaching proper exhaustion levels. Conventional interval training methods also have the limitation that an individual subject may not be equipped with the capability to predict the level of effort required to provide an optimal training intensity.

Our game-like and social networking application with a music recommendation system on a light and small smartphone can be used to prompt participation in the interval training without any large or expensive equipment. The performance of the user can be measured by sensor readings, specifically accelerometers embedded in the iPhone. Additionally, the exercise information of the user is sent to the user's friends group. Our experiments show that customized interval training schedules and commands generated based on the user information increase the accuracy of the interval training up to 88.71%.

A content-based, context-aware, and Bayesian networks-based collaborative filtering algorithm incorporates user music preferences and the exercise speed to play music to enhance performance. Based on user information combined with the information of other individuals in the same group and the speed of the interval training, the list of recommended music is generated and evolved. The experiment shows that the

Bayesian networks-based collaborative method is better for recommending exercise music than the intersection methods. As more data related to the music is accumulated, the experiments show improvement in the selection of recommended music.

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