Original Article

Multi-functional Health Monitoring System

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Based on the statistics of previous years, a major reason for death occurring in patients being cared for at home and residential assisted living facilities is accidental, often resulting from negligence of the relatives or caregivers and resulting in harm to already fragile human beings. As populations continue to age and the birth rate shrinks, the number of chronic patients is expected grow, a rapidly increase in need for drugs for the chronically ill will occur, as well as the increase in accidents related to future lack of the human resources to monitor and care for these patients and resulting in an increase in accidental deaths. These future problems will be worsened if we do not update the current health monitoring system, which is operated manually, which makes use of expensive equipment, and which is performed quite slowly. Given the increases in the chronically ill ages, it is likely in the future that dozens of elderly people will just have one caregiver among them.. Hence, this paper proposes a multi-functional health monitoring system to provide better and safer monitoring than traditional human care. The system includes such hardware as RFID devices to monitor hand temperature, ambient temperature and humidity, a blood pressure and pulse detector to monitor blood pressure and pulse, and a webcam to monitor human expression and age. All information collected by such sensors can be integrated and processed with an embedded system. Using a rule-based decision method, such a system should be able to evaluate a patient's state of health. Should the system detect an unstable status, it can send warning messages to related staff caretakers who could then take the necessary actions to care for the patient in distress in a timely manner. This system would save patient-to-patient monitoring time and allow caretakers to provide immediate care to those in more urgent need of it. Our tests of this proposed system suggest that that it is possible to set up a complete health monitoring system by combining this embedded system and system-alerted health-care service.

Key words: RFID, Facial expression detection, Face aging detection, Embedded system.

Introduction

With the advancement of medical technology and continuous prolonging of the average life-span of mankind, the population of the world continues to age. According to an investigation by the UN, the world population of senior citizens turning 60 will range from 15% to 20% by 2020, while the aging population in Asia will double. This aging will bring forth many problems of health care and increase the prevalence of chronic illnesses and the world's needs for medications.

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First, elderly patients, particularly those with chronic conditions, require continuous long-term monitoring to detect changes in their condition as early as possible[1]. Most research activities[2-5] have been focused on achieving common platform for medical records, monitoring health status of the patients in a real-time manner, improving the concept of online diagnosis, enhancing security and integrity of the patients, developing or enhancing telemedicine solutions, which deals with remote delivery of health care services applying telecommunications, etc.

Facial detection[6-10] mainly adopts skin color detection combined human face feature extraction, with HSV and YC_bC_r color space being the most used to achieve skin color detection. In human face feature extraction, the ellipse detection combination with eye and mouth detection is most used to confirm human face areas after skin color detection. In human expression and human face age detection[11-15], after human skin color block is obtained and after some pre-processing, some useful feature information can be extracted from the block, e.g. eyebrow, eye, nose or mouth. These features change when expression is shown in human face, so they are called action units (AU) [16-20]. These AU points are used to define facial expression. Most often happiness, anger, or being upset provide the basis of inputting the facial expression. Some studies[21-32] propose a feature extraction method based on texture analysis to provide the basis for detecting face age, though Gunay[29] reports age detection to have a lower success rate.

Radio frequency identification (RFID), a non-contact self-identification technology which features the collection of data in a real time and dynamic way, has developed into a major health care technology and is used in various medical industries. Health status indicators like hand temperature, physiology temperature or heart beat can be measured by RFID at any time, allowing 24-hour monitoring. Though a little expensive, if it is integrated into a complete health caring system, the convenience and practicability of RFID will produce values that are far higher than the cost of introduction. Also, RFID applied to into old people with dementia not only provides a structural dementia evaluation system for the clinics, but also has a good command of their cognition capability[33]. This study uses the technology of RFID to measure the physiology values of people under care, making medical care fully automatic and convenient for each user of an all-directional health care system.

Subsequently, we will talk about a so-called “embedded system,” which is a kind of system involving “the embedding of a controller specifically applied and designed for a specialized computer system.” It is the device for control, supervision, or auxiliary equipment, machinery, or device for factory operation. For a novel embedded system, they can be often found in health-care systems[34], cellphones, personal digital assistant (PDA), global position systems (GPS), set-top-box, embedded sever, and thin client. At present, the embedded system has become prevalent in the domain of electrical appliances. The features of such systems are that there are no external connection components, that they have specific functions, that they have small capacities, and that they are highly stable. A great number of embedded systems are being used on the supervision of mobility positioning for elderly men[35]. The system uses an embedded system as its development platform to undertake research on mobile position and care system, primarily to be used on elderly men outdoors. The application of this system can, in the future, be extended onto children or further into motorbikes and vehicles, and it is a very practical system with a great many uses.

There are several groups that aim at building platforms for real-time remote health monitoring. Examples are Rifat[36], Valerie[37], Ren-Guey[38], S.Josephine[39], and Abderrahim[40]. These solutions use (wearable) wireless bio-sensors to monitor patient's vital signs (e.g. ECG, oximeter, blood pressure), environmental sensors (temperature, humidity, and light), and a location sensor. These methods can all be integrated into a Wearable Wireless Body/Personal Area Network (WBAN/WPAN). This type of network consisting of inexpensive, lightweight, and miniature sensors can allow long-term, unobtrusive, ambulatory health monitoring with instantaneous feedback to the user about the current health status and real-time or near real-time updates of medical records.

In summary, some researchers have contemplated the possibility of incorporating optical devices and combining them with sensing technology, though we have discovered that they have some existing problems. First, they did not seek healthcare professional for consultation. In this paper, we use questionnaires to obtain the suggestions of professional people, including doctors, nurses and so on. Secondly, these groups have not used visual techniques in their systems. In our system, the human face expression recognition and human age detection are used.

This paper is organized into the following sections. Section 2 introduces our system architecture. The system algorithm is described in Section 3. The performance analysis and results of our system is described in Section 4 and conclusions are discussed in Section 5.

System Architecture

System hardware architecture

The hardware structure of this system is shown on Figure 1, including the embedded system and RFID temperature and humidity senor device, RFID reader, RFID tag, blood pressure and pulse detector, the automatic control circuit of blood pressure and pulse detector, and network camera. Our proposed system can be used in home care or health care centers. It can be placed by the patient's bed. The blood pressure and pulse detector and hand temperature sensor can be worn on the hand

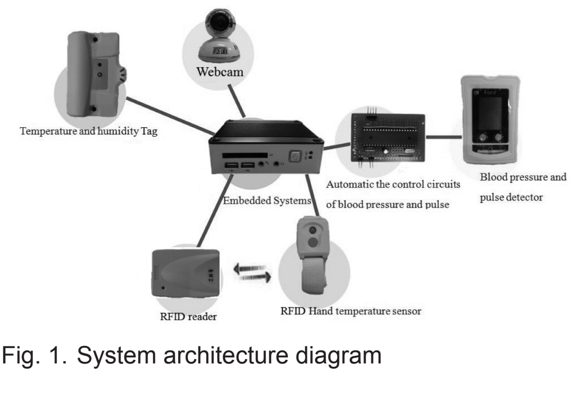


Fig. 1. System architecture diagram

of cared person. RFID temperature and humidity sensor are placed in appropriate places within the room. A webcam is placed in appropriate place that can take frontal face images of the patient. Currently, ultra-small cameras offering large resolution are being manufactured, so patients will not feel that they exist. Nor will they affect patients' perception.

First of all, the device will drive network camera to the embedded system, and then it will process the test subjects' images. Meanwhile, RFID is also integrated into the embedded system. The wrist RFID tag is placed on the patient so that RFID reader can take the temperature. Furthermore, RFID temperature and humidity sensor will speed-examine the temperature information of the patient to see if their temperature is either too high or low. From the system, we can then tell if it is necessary to send out a warning and or store the above-taken information into a database so that doctors can reduce long-term observation and follow-up.

System software architecture

The flow chart of software system is shown on Figure 2. First of all, a patient will wear a RFID wrist tag to measure hand temperature and a blood pressure and pulse detector. Next, indoor temperature and humidity sensor and webcam are turned on so that figures obtained from RFID wrist tag, blood pressure and pulse detector, temperature and humidity sensor, and image extracted from webcam can be transmitted to the embedded system for information analysis and recording. At the same time, human face detection technology is used to detect and mark out human face and then identification steps of human facial expression are conducted to determine human facial expression. Afterwards, when the position of human face is located, the positions that are more likely to generate wrinkles are framed out, such as eyes, nose, and two sides of mouth. A learning algorithm is used to determine age of the human face.

In Figure 2, we implement face detection method using RGB-H-C_bC_r and ellipse detection. Our decision method is based on the knowledge of medical professionals. The controller of the blood pressure and pulse detector is manufactured by ourselves. We propose that two texture features be

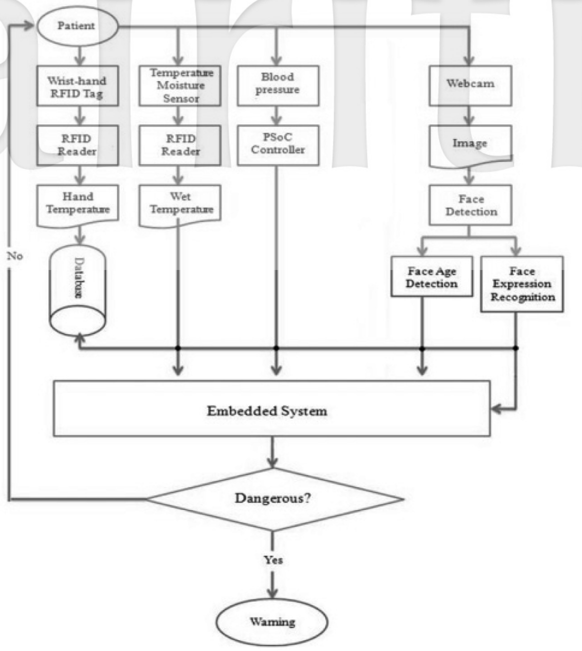


Fig. 2. Flow chart of software system

used to detect face age. Although the extraction method of these two texture features has been used, their integration is a new idea.

Why do we add the human facial expression to our proposed health monitoring system? Generally, machine perception is not as sensitive as human perception. And, because the sensing ability of hardware of physiological signal sensor and our proposed decision mechanism are limited, our system will not be able to detect dangerous status when there is slight body discomfort. However, because the, human body, itself can feel this slight discomfort, the human face will respond or express it. Hence, we add the facial expression recognition method to our system. The method can improve safety and include perception of the patient.

The system will determine if the patient is in a dangerous status or not. If considered in danger, the system will send out an alert; if not, it will resume monitoring. In addition, hand temperature, blood pressure and pulse, heart rate, human facial expression, and their age as well as other information recorded will be integrated into the database, using chart to display the results of daily measurements.

Market analysis

We obtained relevant data from questionnaire survey in order to understand the needs and acceptability in the present market. The questionnaires were sent out to hospitals, and 190 effective questionnaires were returned in total. Its distribution to medical care givers, information staff and others (including patient, acute patient relatives) can be seen in Figure 3 (a).

The tools used in this study are structured questionnaires. Item analysis, market analysis and cost analysis were conducted in the form of Likert scales. The questionnaire includes services relevant to health monitoring system and feelings of the users. Cronbach-α-coefficient was performed for internal consistency reliability analysis. Face validity was used to analyze content validity, expert validity as well as construct validity. First, in the expert validity analysis, five people, including experienced nurses, clinicians, statistical experts, and nursing professors, reviewed content validity for “basic information,” “differences in occupations in health monitoring system,” and “differences in ages in health monitoring system.” The content of review was drawn up based on the status of the patient. The contents of questionnaire are reviewed according to research objective. These contents include the relevant and appropriateness of content, the appropriateness of wording, and the coverage of content. The reviewers used a 5-point Likert scale to evaluate the appropriateness of each item.

1 point: very unsuitable, meaning the item does not make sense and should be deleted.

2 points: doesn't fit, meaning the item does not require a substantial degree or needs a major revision.

3 points: appropriate, meaning the item should be retained, as it is meaningful but requires minor revisions.

4 points: very appropriate, meaning the item is necessary and applicable, but requires minor revisions.

5 points: very fit, meaning the item is correct and necessary. It cannot be omitted.

Average expert's judgments ranged between 4 and 5 points. The experts' opinions were collected

Table 1. Differences in Occupations in Health-Care System

Question	Skewers	Kurtosis	Single issues associated with the total score
Q1: You have been bothered about the negligence of medical care.	-.040	-.78	.30
Q2: You think a health-monitoring system should notify the medical staff immediately.	-.497	1.07	-.327
Q3: You think a health-monitoring system needs to identify patient.	.596	-.87	-.32
Q4: You think a health-monitoring system needs to give correct health and educational information to the patient.	.437	.752	.396
Q5: You think a health-monitoring system should offer various physiology measurement information.	.111	.53	.47
Q6: You think a health-monitoring system needs to store historical physiology messages.	-.643	.152	.107
Q7: You think a health-monitoring system needs the instantaneity.	-.762	.291	-.578
Q8: You often use health-monitoringsystems.	-.296	.496	-58
Q9: You think a health-monitoring system should have the function of sending alarm in real time, alarming the medical staff and relatives.	-.539	-.12	-.413
Q10: You think a health-monitoring system must ensure patient safety and privacy.	-.192	.523	-.346
Q11: You think a health-monitoring system should be easy to operate.	.232	.463	-.301

and used to correct the content and diction of questionnaire.

Next, to determine face validity, we invited 10 nursing staff members and 10 patients to perform pre-testing for "basic information," "difference on occupations in health monitoring system," and "differences on ages in health monitoring system." The items were then revised for the unclear meanings or difficulties in answering based on their responses.

Table 2. Differences in Ages in Health-Care System

Question	Skewers	Kurtosis	Single issues associated with the total score
Q16: You have been bothered about the negligence of medical care.	-.022	-.26	.743
Q17: You think a health-monitoring system should notify the medical staff immediately.	0.105	-.13	.732
Q18: You think a health-monitoring system needs to identify the patient.	-.12	1.96	.640
Q19: You think a health-monitoring system needs to give correct health and education information to the patient.	.134	1.21	.731
Q20: You think a health-monitoring system needs to offer various physiology messages.	.380	1.90	.623
Q21: You think a health-monitoring system needs to store historical physiology messages.	.119	1.11	.571
Q22: You think a health-monitoring system needs instantaneity.	-.752	1.08	.743
Q23: You often use a health-monitoring system.	-.417	1.42	.664
Q24: You think a health-monitoring system must have the function of sending alarm in real time, alarming the medical staff and relatives.	-.529	.489	-.759
Q25: You think a health-monitoring system must ensure patient safety and privacy.	-.692	1.55	.697
Q26: You think a health-monitoring system should be easy to operate.	-.470	.463	.69

Table 3. Cronbach's α coefficient table of each dimension in reliability.

Dimension Name	Cronbach's α value
Difference in Occupations in Health-Care System	.852
Differences in Ages in Health-Care System	.836

The reliability analysis of this questionnaire results were good and within the acceptable range. And, the validity of this questionnaire was satisfactory.

As can been seen in Figure 3 (b), based on our results, we found no matter if it is a medical staff member, information staff member or others (including patient or acute patient relatives), there was willingness to utilize the system. Eighty-three percent of those returning questionnaires were willing to use this system. Two hundred questionnaires were sent out; the effective return ratio was 95%. As shown in Figure 3(c), 82% found it necessary to develop this system, meaning they found it feasible and practicable.

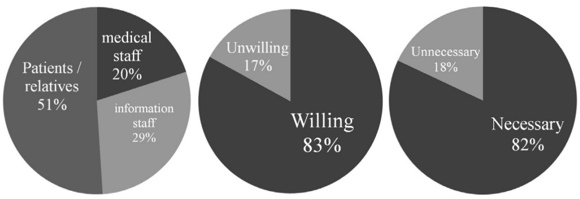


Fig. 3. (a) Distribution of questionnaire targets, (b) distribution of questionnaire willingness, and (c) necessary distribution of system development.

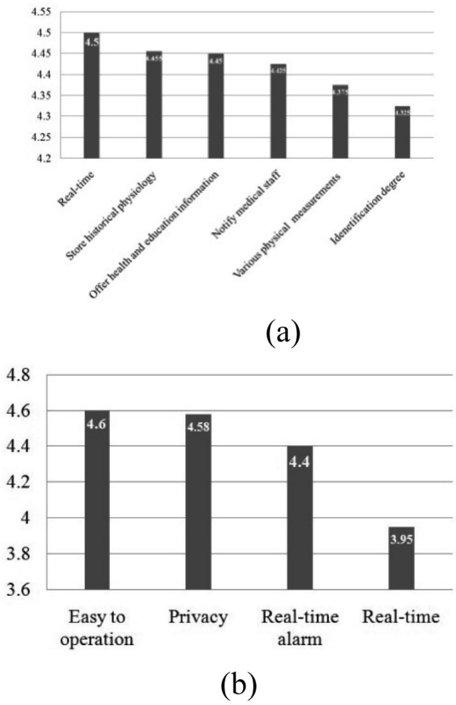


Fig. 4. (a) Statistical diagram of system functional emphasis, and (b) statistical diagram of system need emphasis.

We used independent sample T test to analyze our data. In order to investigate which functions in health monitoring system were the most important to our sampled parties, we averaged the Likert points from all 190 effective questionnaires. Any item with an average Likert point above 3 was considered to be of great importance. The second most important function was its real-time feature, followed by its storage message history, provision of health and education information, notification of medical staff, provision of various physiology measurements and degree of identification (Figure 4a). A statistical analysis was then conducted on the health care system with regard to needs. From this perspective, easy operation was believed to be the most important, followed by privacy, real-time alarm, real-time information (Figure 4b).

As shown in Table 4, among the differences in occupation for health monitoring system, there was often no significant differences the answers to the various items except for one item Q8 "You often use health monitoring system." The reason for the significant difference for this item is that medical staff members use health monitoring systems to care for patients more than ordinary people.

Table 5 is an analysis table for age differences. It shows significant differences with p value in independent sample T test less than 0.05 among four items, e.g. Q16 "you have been bothered about the negligence of medical care," Q17 "you think a health monitoring system should notify the medical staff immediately," Q23 "you often use the health monitoring system," and Q27 "the biggest concern in the health monitoring system is instantaneity."

The reason for these differences is medical negligence often arises in the health monitoring system experiments for the elderly users. The medical staff does not receive notice of negligence

Table 4. Differences in Occupations in Health Monitoring System

Questions	p-value
Q1: You have been bothered about the negligence of medical care.	0.782
Q2: You think a health-monitoring system should notify the medical staff immediately.	0.915
Q3: You think a health-monitoring system needs to identify the patient.	0.155
Q4: You think a health-monitoring system needs to give correct health and education information to the patient.	0.693
Q5: You think a health-monitoring system should offer a variety of physiology measurements.	0.533
Q6: You think a health-monitoring system needs to store historical physiology messages.	0.712
Q7: You think a health-monitoring system needs the instantaneity.	0.862
Q8: You often use health-monitoring system.	0.035*
Q9: You think a health-monitoring system should have the function of sending alarm in real time, alarming the medical staff and relatives.	0.185
Q10: You think a health-monitoring system must provide patient safety and privacy.	0.168
Q11: You think a health-monitoring system should be easy to operate.	0.926
Q12: The biggest concern is instantaneity in a health-monitoring system.	0.497
Q13: If this system is established, you are wiling to try this system.	0.101
Q14: You think the establishment of health-monitoring system is necessary.	0.586
Q15: You think a health-monitoring system increases the convenience of caring.	0.852

* represents that there is a significant difference.

the first time it occurs.

The above table is a market survey made for our health monitoring system. We will continue to analyze these findings and improve upon them by sending more questionnaires with the hope of bringing the users a reasonably priced and practical health monitoring system capable of reducing medical negligence and improving care quality.

System Algorithm

This section will give a detailed description of the human facial detection, human age detection and identity identification.

Table 5. Differences in Ages in Health Monitoring System.

Questions	p-value
Q16: You have been bothered about the negligence of medical care.	0.034*
Q17: You think a health-monitoring system should notify the medical staff immediately.	0.045*
Q18: You think a health-monitoring system needs to identify the patient.	0.567
Q19: You think a health-monitoring system needs to give correct health and education information to the patient.	0.856
Q20: You think a health-monitoring system needs to offer various physiology measurements information.	0.813
Q21: You think a health-monitoring system needs to store historical physiology measurements information.	0.954
Q22: You think a health-monitoring system needs instantaneity.	0.557
Q23: You often use the health-monitoring system.	0.043*
Q24: You think a health-monitoring system must have the function of sending alarm in real time, alarming the medical staff and relatives.	0.250
Q25: You think a health-monitoring system must maintain patient safety and privacy.	0.705
Q26: You think a health-monitoring system should be easy to operate.	0.145
Q27: The biggest concern is instantaneity in a health-monitoring system.	0.001*
Q28: If this system is established, you are willing to try this system.	0.982
Q29: You think the establishment of health-monitoring system is necessary.	0.817
Q30: You think a health-monitoring system increases the convenience of caring.	0.981
Q31: You think a health-monitoring system can solve the problem of online caring.	0.034

* represents that there is a significant difference.

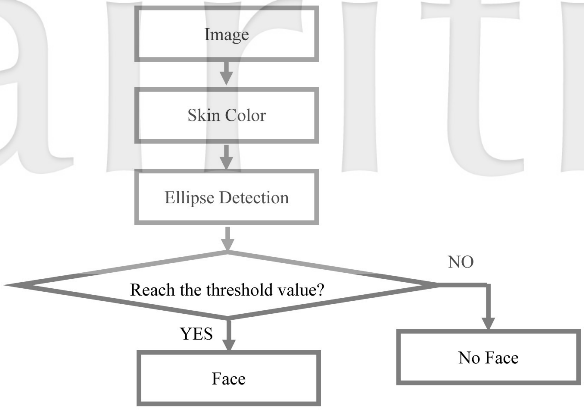


Fig. 6. Flowchart of face detection

Detection of human face

The detection on facial locations is the primary step in identifying experession and age. This study used skin color information as the basis of detection. As can be seen in Figure 6, human facial detection is divided into two steps: skin color detection and ellipse detection. For skin color detection, we used RGB-H-C_bC_r [8] alligation to detect the area of skin color. Briefly, we first made a color image, converted it through RGB to HSV and RGB to C_bC_r, marked the scope of selecting skin color most suitably according to the characteristics of color space, and finally an new color space RGB-H-C_bC_r is obtained by intersecting the three color spaces.

Because there are many blocks in skin color detected from the image, smaller skin color blocks were gradually combined using a morphology algorithm. We then recorded the blocks not belonging to the same skin color by marking them. We then found the blocks with most marked values to be a candidate blocks of human face. After this was done, we selected the blocks of human face from these candidate blocks. Facial detection was then finished using ellipse detection [32].

The place in among skin color candidate blocks that looks like ellipse was considered the human face. Basically, this method is based on the template matching method. This ellipse template decides its shape and size by long and short axle. Because the projected size of human face is relevant to the distance between human and video camera as well as the size of human face, in order to respond the changes of projected size of human faces in the image, the size of ellipse template must vary accordingly. The rate between long and short axle of ellipse formed by human face is approximately $\frac{y}{x}$=1.2, where y is the long axle of template, and x the short axle of template. Based on such percentages, the search space may be zoomed in and out. Figure 10 shows the ellipse detection result.

Fig. 10. the search results of ellipse template

Obtaining the Characteristics Points of Human Face

Before we could identify facial expression and human face age, we had to capture the facial characteristics. The characteristics points that can represent the human facial expression changes and age were obtained and used as the basis of judging human facial expression. Two characteristics points were included: the five-organ feature point and texture.

Extracting the Five-organ Feature Points

A. Eye Feature Extraction

Based on Sanjay Kr [14], the height of human face is about 1.2 times the width of human face. According to the proportion of facial features, the location of the pupil falls between 4 / 12 and the 7 / 12 region of the height of human face if the beginning is on the top of the face. The location of the pupil also falls between 2 / 16 and 15 / 16 region of the width of human face if the beginning is on the left of the face. We focused on this area to find out the pupil formula. Figure 11(a) shows the extraction algorithm of eye, 11 (b) the original image, and 11(c) the result of binarization of pupil area.

In the above algorithm, F_W represents short axle of ellipse, F_H represents long axle of ellipse, *f(x,y)*represents pixel matrix within ellipse, *pupil(x,y)* represents the matrix of storing pupil. When *pupil(x,y)*=255, it represents a pupil point; otherwise, (*x,y*) is not a pupil. Combining *pupil(x,y)*

$$If\ (\frac{2}{16}F_W \le x \le \frac{5}{16}F_W \ \ and\ \ \frac{4}{12}F_H \le y \le \frac{7}{12}F_H)$$

```
{
    If  f(x, y) == 0;
    {
    pupil(x, y) = 255;
    }
    else
    {
    pupil(x, y) = 0;
    }
}
```

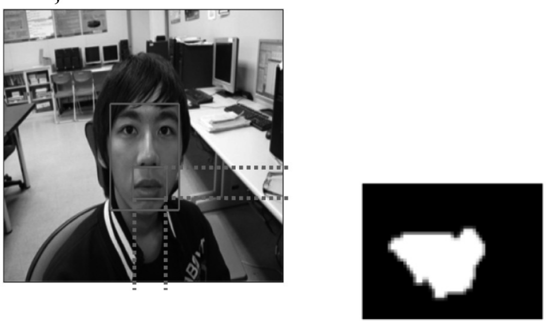
(a)

(b) (c)

Fig. 11. (a) the feature extraction algorithm of eyes, (b) approximate region of the eyes, and (c) binarization result of pupil region.

$$If\ (\frac{7}{10}FN_w \le x \le \frac{9}{10}FN_w \ \ and\ \ \frac{2}{6}FN_H \le y \le \frac{5}{6}FN_H)$$

```
{
  If  (h - h0 < w)
  {
  f(h) = (1 - (h - h0)^2 / w^2) * 100;
    If  (h 50 < f(h)  and  f(h) < 100)
    {
      Nose(x, y) = 255;
    }
    else
    {
      Nose(x, y) = 0;
    }
  }
  else
  {
  f(h) = 0;
  }
}
```



(b) (c)

Fig. 12. (a) feature extraction algorithm of mouth, (b) general mouth zone, and (c) the binarization result of mouth zone.

and image projection method, we could find the coordinates of pixel points in uppermost and lowermost side for pupils in right and left side. Using these two coordinates, we could also find the coordinates of pixel points in most left and most right sides.

B. Mouth Feature Extraction

Based on Sanjay Kr[14], we could fix the position of the mouth in the face. To separate color and brightness, we converted the face image from RGB color space to HSV color space. The images were not subject to the impact of external light. The H value was converted as follows:

$$f(h) = \begin{cases} 1 - \frac{(h-h_0)^2}{w^2} & |h - h_0| \le w \\ 0 & |h - h_0| \ge w \end{cases} \quad (1)$$

In the above algorithm, FN_W represents short axle of ellipse, FN_H represents long axle of ellipse, *Nose(x,y)* represents the matrix of storing all mouth positions. *h* represents *h* value in mouth area, h_0 represents displacement value defined on the basis of color, set out as 1/3. The *w* is set as 0.60. This equation suggests that the acceptable scope is filtered by centering h_0 and using *w* value. The farther the h value in mouth area is from h_0, the smaller *h* value. *f (h)* value ranges from 0 to 1. Figure 12 (a) shows the whole algorithm and Figure 12 (c) shows the mouth detection result.

In this study, we used the color red to detect the mouth, so any color similar to red around the mouth area might be cause noise and affect the mouth feature results. Thus, we used the closing

(a) (b)

Fig. 13. (a) The binarization result of mouth, and (b) is 4-connected component result.

(a) (b)

Fig. 14. (a) result of mouth binarization, and (b) result of 4-connected components.

processing of morphology technique on the binarized image in mouth zone to create a more complete mouth area. Then, we used 4-connected component method to find the largest area and removed the causes of noise.

There was a problem that arose when trying to find the largest area. When people are laughing, the upper lip does not connect to lower lip. At the moment of laughter, we might be catch lower lip area only. Hence, in this situation, we can also obtain the 2nd largest area. This 2nd largest area must be above the largest area and the value should be very close to value of the largest area. Otherwise, we only kept the largest area. Figure 14 (a) shows the result of mouth binarization, and Figure 14 (b) shows the result of 4-Connected Component.

Because the mouth tends to have a horizontal edge, we used horizontal Sobel filter to get the horizontal edge of mouth area and binarize it. Then, from left to right of image, we found the 1st point where both the pixel value of binarized mouth image and binarized mouth image obtained by Sobel filter processing are 1 and marked the point as feature point G. From right to left of image of image, we found the 1st point where both the pixel value of binarized mouth image and binarized mouth image obtained by Sobel filter processing are 1 and marked the point as feature point I. We

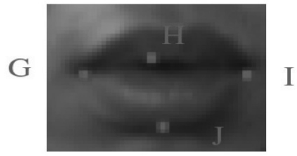


Fig. 15. Results Sobel binarization of the mouth
Fig. 16. Feature points of the mouth

found two vertical feature points from two pixels extension to the left and right from the center point of the two horizontal points, making 5 horizontal pixels. From these 5 horizontal pixels, we looked for the 1st point where both the pixel value of binarized mouth image and binarized mouth image obtained by Sobel filter processing were 1 from top down, and marked the point as feature point H. From bottom to top, in these 5 horizontal pixels, we found the 1st point where the pixel value of binarized mouth image obtained by Sobel filter processing was 1 and mark this point as feature point J.

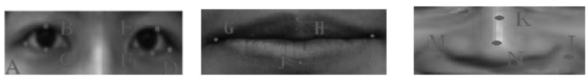
C. Nose Feature Extraction

The nose is located in the center of gravity of eyes and mouth. After obtaining ten AU (action unit) points from eyes and mouth, we separately took each AU point of eyes and mouth to find the center of gravity of triangle. Through the proportion of eyes and mouth feature as determined by equation (2) and equation (3), we could find the location of the nose.

$$X_{nose} = \frac{X_{Leye} + X_{\mathrm{Re}ye} + X_{mouth}}{3} \tag{2}$$

$$Y_{nose} = \frac{Y_{Leye} + Y_{\mathrm{Re}ye} + Y_{mouth}}{3} \tag{3}$$

Based on equations (2) and (3), we used the feature points from eyes and mouth to obtain the center of nose. We useed feature point of the center to be the center of gravity of triangle of nose, and the feature point of mouth and eyes to get the location of three climaxes of triangle (Fig. 17).



(a) (b) (c)

Fig. 17. (a) eye feature points, (b) mouth feature points, and (c) nose feature points.

Extracting Texture Feature Points

After the features of the five organs were extracted, we used the Local Binary Patterns (LBP) and Laws' Mask to extract the texture features of faces. The objective was to obtain human age.

A. LBP Feature Extraction Method

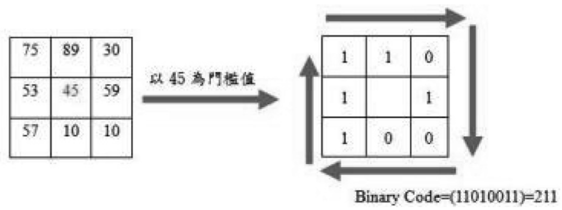
We based LBP feature extraction for age detection on methods used by Y. Fu[24] and Gunay[25]. LBP features are used to describe the characteristics of regional changes in texture calculations. This method has the advantage of being simple, fast, and free from shadow problems. This method is popularly used in face detection research in.

$$LBP_{P,R}(x_C)=\sum_{P=0}^{P-1}u(x_p-x_c)2^P,\quad u(y)=\begin{cases}1, & y\geq 0\\ 0, & y<0\end{cases} \tag{4}$$

In equation (4), represents the center pixel. The P, R is the radius. When R = 1, its P = 8; When R = 2, its P = 16; When R = 3, its P = 24. By changing the radius (R) and neighbors (P) can show the texture of a larger structure.

LBP processing can be demonstrated using Block of 3*3 as an example case. First, color images were converted into grayscale images. Assuming that the image gray value of a block is as shown in Figure 18 (a), the center gray value of 3*3 block was set as threshold value. If the eight points around the threshold value were greater than the threshold value or equal to the threshold value, the point was set to 1. If not, it was set to 0. Figure 18 (b) shows the processing result.

Certain areas are prone to wrinkles. These include the areas around the eyes, nose, and both sides of the mouth. As can be seen in Figure 19, both sides of the AU can point out the captured expansion. The eye area is indicated by the



(a) (b)

Fig. 18. (a) id gray value of block and (b) is LBP operator.

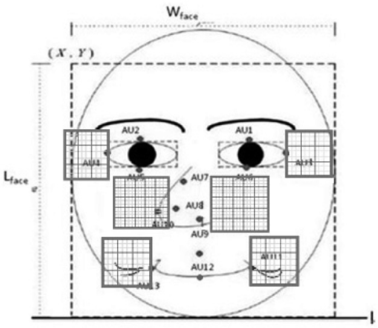


Fig. 19. facial feature points (AU) of the diagram

outward expansion into AU3 and AU4 size (R = 5 and P = 40), the nose by both sides of the regional expansion of the AU10 and AU9 out into the size (R = 7 and P = 56), and both sides of the mouth area by the AU11 and AU13 outward expansion into the size R = 5 and P = 40). These regions to the center are considered the threshold value by the LBP feature extraction. They were used to find uniform patterns belonging to the regional characteristics. After storing a record of the values, they were inputted to neural network as training data.

B. Laws' Mask Feature Extraction Method

We used Laws' mask to extract texture, and feature values were obtained based on the principle of texture energy. The variables included five masks: edge, level, spot, ripple and wave. These masks are expressed in the equation (5). Using this 5 one-dimensional shielding, we can obtain 25 two-dimensional mask combinations.

E5= Edge detection: [-1 -2 0 2 1]
L5= Level detection: [1 4 6 4 1]
S5= Spot detection: [-1 0 2 0 -1]
R5= Ripple detection: [1 -4 6 -4 1]
W5= Wave detection: [-1 2 0 -2 1]

Next, we could perform equations (6) to (9) using the 25 two-dimensional masks as follows:

$$TI_{E_5E_5}=I_{ij}\otimes E_5E_5 \tag{6}$$

$$Normalize(TI_{mask})=\frac{TI_{mask}}{TI_{mask}} \tag{7}$$

$$TEM_{ij}=\sum_{u=-7}^{u=7}\sum_{v=-7}^{v=7}\left[Normalize\ (TI_{i+u,j+v})\right] \tag{8}$$

$$TR_{E_5L_5}=\frac{TEM_{E_5L_5}+TEM_{L_5E_5}}{2} \tag{9}$$

After equation (9) was performed, we used these results to extract five texture feature values: Mean, SD, Skewedness, Kurtosis and Entropy. These five features were used to estimate age. Afterwards, a neural network learning algorithm was used to determine the age of human faces. Equations (10) to (14) are the calculations of the five features values, where represents the unchangeable values within 25 masks from TEM before and after rotation, and the size of whole image.

$$Mean = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}\left[TR_{ij}\right]}{M \times \mathrm{N}} \tag{10}$$

$$SD = \sqrt{\frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(TR_{ij} - Mean)^2}{M \times \mathrm{N}}} \tag{11}$$

$$Skewness = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(TR_{ij} - Mean)^3}{M \times \mathrm{N}} \tag{12}$$

$$Kurtosis = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(TR_{ij} - Mean)^4}{M \times \mathrm{N}} - 3 \tag{13}$$

$$Entropy = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(TR_{ij})^2}{M \times \mathrm{N}} \tag{14}$$

Human Face Expression Recognition and Age Detection

A. Recognition algorithm: After the feature points were captured, human facial expression could be recognized. Here it is finished by applying back-propagation neural network (BPNN) learning algorithm.

B. Parameter description of two recognitions

(1) For human facial expression recognition, we used 28 input neurons, which were X coordinate and Y coordinate in 14 feature points found from a human face image. Hidden layer uses 15 neurons, and output layer uses 2 neurons. Because one neuron can represent 0 and 1, two neurons can represent four expressions, including happiness, anger, upset and pleasure.

(2) For human face age detection, the characteristics obtained from two features extraction methods LBP and Laws' mask were put into back-propagation neural network, e.g. two eyes, eye end, nose and corner of mouth. Input layer used 110 input neurons, which are X coordinate and Y coordinate in 110 feature points found from a human face image. Hidden layer uses 111 neutrons, and output layer uses 2 neutrons. Two output neurons represent the results within the scope of 0-30 years, 31-50 years, 51-70 years and more than 70 years.

Patient Identity Identification and Physiology Signal Value

To measure body temperature, a patient was given a wrist-type RFID TAG, each given an exclusive number and used to identify the patient.

For indoor temperature and humidity sensor and body temperature sensor, hand temperature was measured by RFID Tag in combination with indoor temperature and humidity sensor. Thus, a double detection was performed. The blood circulation of human body requires metabolism to a certain extent, and extreme environmental temperatures may exert big influence on the metabolism. Under ambient temperatures suitable for human body, the metabolism rate stays stable. Relatively speaking, if room temperature is not suitable, the normal metabolism function may be affected. Hand temperature and room temperature were detected by using this system, providing the caregiver information about possible abnormality in body temperature of the patient. After body temperature information is received by RFID Reader and using RFID technology, it is delivered every 15 seconds, and the temperature information of patient's room is inputted into embedded system once, giving the caregiver access the newest information in real time.

For blood pressure, because an arm inflation apparatus is worn during blood pressure measurement, it may cause inconvenience to the users who are restricted to the bed for long periods of time. Therefore, we used self-made the control circuit of blood pressure and pulse device to automatically control the blood pressure and pulse detector. The control circuit uses the programmable system-on-chip (PSoC) to do this. PSoC is a programmable mixing signal digital unit framework, controlled by a micro-control unit that is built with chips inside, which integrates configuration analog and digital circuit and is composed of dozens of components, including UART, timer, amplifier, comparer, digital to analog converter (ADC), filter, etc. This control circuit automatically initiates the blood pressure and pulse detection once an hour. A seven-segment display is added to display the residual initialization time. LCD display shows the use status of blood pressure detector at present at any time, buzzes to notify the user and medical staff five minutes before each measurement is initiated. The blood pressure value is returned back to the embedded system for analysis and processing through USB transfer lines.

Rule-based Decision Method

To make final decisions based on the above extracted data, we first transmit data (hand temperature from RFID tag, the value of systolic and diastolic pressure from blood pressure and pulse detector and the value of environment temperature and humidity from temperature and humidity sensor to embedded system) to our embedded system. Next, we use rule-based decision technology to judge whether the status of patient is in the normal range for his or her age group or not. The total number of rules was 36. Four rules are listed below as examples.

$\boldsymbol{R^1}$: *If* $T_{hand}+8^o>38^o$ *and* $24^o<$ *Teviron* $<27^o$ *and*
60< Heartbeat <100 and
45< Humidity <55 and
60< diastolic pressure <80 and
100< systolic pressure <120
Then, status is a little fever.

$\boldsymbol{R^2}$: *If* $36^o<$ *Thand*$+8^o<37.5^o$ *and* $24^o<$ *Teviron* $<27^o$ *and*
60< Heartbeat <100 and
45< Humidity <55 and
50 mmHg < diastolic pressure <60 mmHg and
90 mmHg < systolic pressure <100 mmHg
Then, status is hypotension.

$\boldsymbol{R^3}$: *If* $36^o<$ *Thand*$+8^o<37.5^o$ *and* $24^o<$ *Teviron* $<27^o$ *and*
60< Heartbeat <100 and
45< Humidity <55 and
80 mmHg < diastolic pressure <89 mmHg and
120 mmHg < systolic pressure <139 mmHg
Then, status is hypertension.

$\boldsymbol{R^4}$: *If* $36^o<$ *Thand*$+8^o<37.5^o$ *and* $24^o<$ *Teviron* $<27^o$ *and*
60< Heartbeat <100 and
45< Humidity <55 and
60 mmHg < diastolic pressure <80 mmHg and
100 mmHg < systolic pressure <120 mmHg
Then, status is normal.

Experimental Results

We used the Microsoft system platform (Windows Embedded CE 6.0 R2). Hardware Specifications are ICOP Ebox-4300 500MHz microprocessor, 512MB Memory, 10/100 Mbps LAN network card, two RS-232 ports, and three USB 2.0 ports. CPU is Intel P4 GMHz specifications and Memory size is 1G RAM.

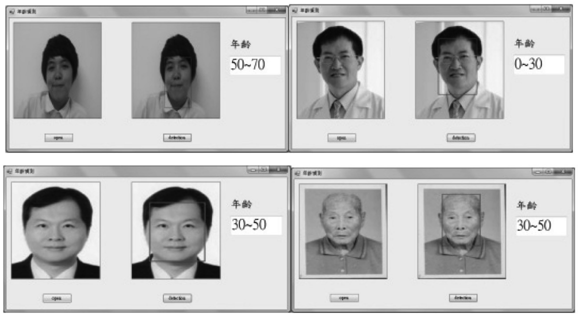
The image resolution was 640x480, and frame rate was 30fps. There were still some mistakes in human face detection due to light and noise. Figure 21 (a) shows successful cases of human face detection and Figure 21 (b) shows failed detections. Failures resulted from skin color range and lighting.

Next, we adopted LBP and Laws' mask, two feature extraction methods, to extract feature point data (AU) for two eyes, eye ends, nose corners and mouth corners. After data was screened for appropriateness, all data were entered into back-propagation neutral network which was trained to identify different age ranges, including 0-30 years, 31-50 years, 51-70 years and more than 70 years. Two hundred static human face expression images were selected and 1100 sets of feature points were entered to train neutral network algorithm and find the optimal weight values. Using this optimal weight value allowed us to know the general age

(a) (b)

Fig. 21. (a) successful detection results and (b) failed detection results

(a)



(b)

Fig. 22. (a) successful detection, and (b) failed detection

of the patients. The system had an age recognition rate of about 85%. The Figure 22(a) and Figure 22(b) show the successful and failed results of recognition respectively. Age detection failure may be attributed to excessive image blurring or excessive exposure during photographing.

Failure to detect the image due to blurred or over-exposed images lead to unsuccessful extracted face textures, making impossible to successfully detect face age.

Subsequently, we used mean absolute error (MAE) measure to evaluate age estimation performance. The MAE of our proposed method on MORPH was 7.11 compared to X Geng [22] 8.83. Finally, an aggregate comparison of MAE values is shown in Table 6 for both FG-NET and MORPH databases.

Fig. 23. extracted facial feature points

Fig. 24. the result of error detection in our system.

Fig. 25. the results of correction detection in our system.

After human age detection, we extracted facial feature points. Figure 23 shows the result of feature point extraction.

Through training in neural network, we obtained the weight values of all kinds of face expression images. When testing, we used 100 static face images of several of facial expressions. Figure 24 and Figure 25 depict successful or failed examples. Table 7 compares the success rate of our facial expression detection method with other methods.

In this system, the patient receives a RFID tag and oxygen pulse detector for the measurement of hand temperature, heartbeat, and blood pressure. Normal hand temperature ranges between 28 and 30 degrees, differing from axillary temperature by about eight degrees. Normal systolic pressure ranges between 140 and 160mmHg, normal diastolic pressure between 90 and 95mmHg,

Table 6. The comparison of MAE of our age detection method and other methods.

Database(DB) / Method	FG-NET	MORPH	Our DB
Nabil Hewahi [28]	8.33	9.06	8.06
X Geng [22]	6.77	8.83	7.57
Our proposed method	**5.97**	**7.11**	**5.07**

Table 7. A comparison of the success rate of our facial expression detection method and other methods.

Database(DB) / Method	FG-NET	MORPH	Our DB
Wang [30]	83.1%	80.8%	82.3%
Zhang[31]	82.9%	80.2%	82.1%
Our proposed method	**83.2%**	**81.0%**	**82.4%**

(a) (b) (c)

Fig. 26. (a) basic user interface, (b) health care system interface, and (c) report form.

and normal heartbeat range between 60 and 100bpm. We set up a webcam to recognize the patient's expression and used back propagation neural network as algorithm of face expression recognition. We had a recognition rate of about 82.4%, with failures due to light affect and face skew, suggesting a need for adjustment for better recognition rates in the future. In fact, we have already used the system to private health care organization for one month. Interviews with people in that organization revealed that the system helped them. Figure 26 based system as the user interface.

Conclusions

It is usually necessary to continually monitor and record multiple physiological signals (such as hand temperature, blood pressure and pulse) of a patient to determine the his or her health status. Hence, in this paper, we proposed a health monitoring system that combines visual techniques with multiple physiological sensors. To do this, we first designed a questionnaire to obtain the suggestions of healthcare professionals. The questionnaire was found to have acceptable reliability and satisfactory validity. Secondly, we used a rule-based decision method to integrate all physiological signals and image information together. Finally, to verify the performance of our proposed system, we implemented a prototype system for testing and evaluation. While not perfect, our proposed method had better facial expression detection and age detection rates than other methods. Therefore, the results of our experiments show that our system can indeed provide feasible and practical health monitoring services, though some improvements are needed.

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Original Article

多功能健康監控系統

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根據歷年資料的統計，許多居家照護的死亡原因之中以意外傷害居多，而其中大部分原因往往是家人或照護人的一時疏忽而釀成了大錯，因而傷害了一個脆弱的生命，且隨著全球高齡化趨勢的發展及少子化現象，可以預見高齡化趨勢勢必衍生出許多健康照護方面的問題及慢性病患人數快速增加和藥物的需求。而目前市面上的的照護系統皆需透過大量人力操作及昂貴的儀器設備，加上人口少子化的影響，可能造成未來一名照護員必須同時間照護數十名老人的情況。因此本論文提出一套結合多項生理訊號感測裝置及視覺辨識技術之健康監控系統，裡面結合RFID技術、血氧脈搏檢測器、人臉表情偵測及年齡辨識等儀器和技術，利用嵌入式系統將感測到的所有資訊作決策判斷，若有危險的狀況產生，系統便會發出警訊通知相關人員，如此可以減少照護人員的辛勞並提供更完善的照護給被照護者。從實驗結果可以了解我們所提出來的系統是一個確實可以被實踐和被使用的系統，且在系統中我們所提出的人臉表情辨識和人的年齡偵測技術比起其他方法有更好的辨識與偵測的結果。

關鍵詞：RFID、臉部表情辨識、年齡辨識、嵌入式系統

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