A Chronic Disease Identification Scheme Using Radar Chart Method for Personalized Healthcare System

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Abstract. Facing to the increasing demands and challenges to personalized disease management, various researches on the personalized healthcare systems which can provide customizable healthcare and patient disease management services have been extensively performed. Among the managed disease, chronic diseases such as metabolic syndrome or diabetes are the main target the long-term diseases care, because the diseases require the real-time monitoring, the multidimensional quantitative analysis, and its classification of patients' diagnosing information. Therefore, to enhance the effectiveness of medical decision process during patient diagnosis, we propose a personalized patient disease identification scheme for effectively diagnosing and show the validity of the proposed scheme.

Keywords: healthcare, chronic disease, radar chart, personalized healthcare.

1 Introduction

Chronic disease becomes an important issue of healthcare systems in many countries. For example, it is forecasted that clinical expenditure for chronic disease in U.S. would be 80% of total medical costs and more that 150 million people might be suffer from chronic disease in 2020. Health status monitoring in out-of-hospital environments particularly patients self-management at home environment has been a major issue of healthcare researchers and developers for long time. Continuous monitoring of health status during daily life activities is essential for effectively managing chronic disease [1]. From a medical service provider's point of view, to provide advanced quality healthcare service for chronic disease, the following issues need to be resolved. Patients require continuous health status monitoring and care over a long term period. Their disease status sometimes may be changed unexpectedly. However, there exist few medical systems that provide any alarm about chronic patient status. The conventional medical examination processes for chronic disease status detection are complicated. The medical systems need to generate reliable outcomes for patients with complex chronic conditions [1]. Therefore, it is important to provide patients with self-management capability and enable patients'

Y.-S. Jeong et al. (eds.), *Ubiquitous Information Technologies and Applications*,
Lecture Notes in Electrical Engineering 280,
DOI: 10.1007/978-3-642-41671-2_3,

own management of disease conditions. The healthcare system are required to assist patients' self-management for chronic condition better through delivering more exact information and suggesting suitable for disease management.

Conventional healthcare systems have focused on providing specific target services only. However, achievements in various ICT technologies have enabled a lot of research on personalized healthcare systems for at home environment. But, the research is mostly focusing on the patients' medication treatment of chronic disease, e.g., to deliver the right treatment, to the right patient, at the right dose and at the right time [2]. Healthcare services, such as health monitoring, medical consultation and so on need to be personalized based on the context of patients' profiles. For efficient provision of personalized healthcare services, it is necessary to accurately identify patients' health status, particularly chronic diseases.

There are several studies for developing personalized disease identification schemes [3][1]. Among them, [1] proposed a novel Patient Status Classification Method (PSCM), which is based on patient tier classification and radar chart priority calculation using surface measure of overall performance (SMOP) theory [4]. The PSCM model for patients with chronic diseases offers automatic medical service procedures in the form of an effective medical information visualization system. It reduces the workload by offering readily available data. The PSCM process contains three parts: the Patient Tier Classifier, the Disease & Complications Identifier, and the Health Risk Quantification [1]. Although radar chart approach (RCA) and SMOP method are very effective ways for identifying goods or best performers while maintain the interdependence of different policy goals in evidence, it is known that those methods have following several weakness [5].

1) Not theory-driven performance indicators
2) Equally weighted performance indicators which are problematic and unjustified
3) No explanation for performance levels, changes and structures of performance
4) No information about efficiency measurement

In order to resolve the weakness of RCA and SMOP above, in this paper, we propose an analytic hierarchy process (AHP) based weighted RCA scheme in order to accurately identify patient disease. We evaluate our proposed scheme by using sample patient physiological data.

In the following sections, the description of proposed patient status classification model for chronic disease care is presented, along with the chronic disease identification procedures.

2 A Chronic Disease Identification Scheme Using Analytic Hierarchy Process and Radar Chart

As we discussed in the previous section, RCA is a very useful method for qualitative data analysis despite of its weakness and it is useful for preliminarily identifying patient's chronic disease and disease status [1]. So, in order to mitigate the weakness

of RCA and SMOP, we have adopted AHP in order to determine the weights of performance indicators and propose a novel patient disease identification scheme based on areal similarity degrees between two radar charts, one displaying the typical characteristics of designated disease by averaging patients medical test results, and the other showing patient's medical test results. We evaluate our proposed scheme by using sample patient physiological data.

AHP is a multi-criteria decision making method developed by Thomas Saaty [6]. AHP allows decision makers to model a complex problem in a hierarchical structure, showing the relationships of the goal, objectives, and alternatives. AHP is made up of several components such as hierarchical structuring of complexity, pairwise comparisons, judgments, an eigenvector method for deriving weights, and consistency considerations. So, we apply AHP to determine the weights of indicators for each medical test results.

Many variables values are put into the same coordinate plane, the area is representation function for the whole quality, and the shape gives the detail characteristics. In the weighted radar chart, every input variable value is expressed by radial r_i of unit circle and w_i is weight coefficient. A circle in which the radius represented input measurement ranges is one could be divided into n parts according to different weight coefficient w_i and the sum of the w_i coefficient is equal 1. On the circle, the n rays represent, the n input variables and the r_i measured value of an input variable will fall in a relevant ray. Connecting the points r_i, which corresponds to measured values of different inputs, a weighted radar chart could be obtained [7]. Since input data for each performance indicator in the weighted radar chart have difference measurement scales, it is important how to transform the original input data to the transformed new input range of weighted radar chart, i.e., transformed input range between zero and one. Since the distribution of medical test results generally follows normal distribution, let the result of i_{th} medical test be x_i and the arithmetic mean and standard deviation of x_i be $E(x_i)$ and $\sigma(x_i)$, respectively. Then, $x_{i_{new}}$, the standardized value of x_i can be written as follows:

$$x_{i_{new}} = \frac{x_i - E(x_i)}{\sigma(x_i)} \tag{1}$$

In order to depict $x_{i_{new}}$ with radar chart whose accepted input range is 0 to 1, it is necessary to transform $x_{i_{new}}$ to new input range. Let $x^*_{i_{new}}$ be the transformation of $x_{i_{new}}$, then $x^*_{i_{new}}$ can be expressed as follows [9].

$$x^*_{i_{new}} = [\tfrac{2}{\pi} tan^{-1}(x_{i_{new}}) + 1] \times \tfrac{1}{2}, \text{ where } 0 \le x^*_{i_{new}} \le 1 \tag{2}$$

Since each medical test result has different influence on disease status, it is necessary to separately weight impact of test results to the disease status. In order to separately weight importance of the types of medical tests, we have utilized the results of risk factor analysis for metabolic syndrome in order to calculate the weights of medical test results. Fig. 1 shows the decomposition of risk factor structure for the metabolic syndrome symptoms based on the correlation analysis results presents in [10].

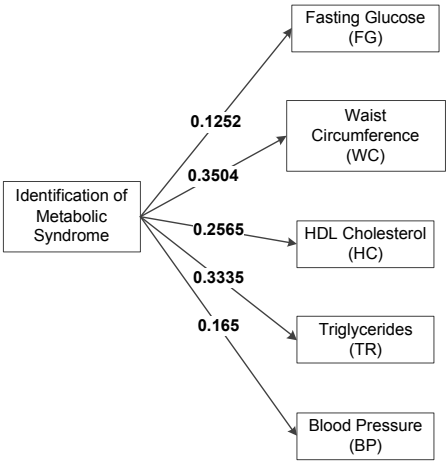

Fig. 1. Decomposition of risk factor structure for the metabolic syndrome symptoms

Pairwise comparison matrix A can be setup based on the hierarchy shown in Fig. 1.

$$A = \begin{array}{c} \begin{matrix} \text{FG} & \text{WC} & \text{HC} & \text{TR} & \text{BP} \end{matrix} \\ \begin{bmatrix} 1 & 0.3573 & 0.4881 & 0.3754 & 0.7588 \\ 2.7988 & 1 & 1.3661 & 1.0507 & 2.1236 \\ 2.0488 & 0.7320 & 1 & 0.7691 & 1.5545 \\ 2.6638 & 0.9517 & 1.3002 & 1 & 2.0212 \\ 1.3179 & 0.4709 & 0.6433 & 0.4948 & 1 \end{bmatrix} \end{array} \begin{matrix} \text{FG} \\ \text{WC} \\ \text{HC} \\ \text{TR} \\ \text{BP} \end{matrix} \tag{3}$$

Where a_{ij} is the relative importance of the i_{th} element in j_{th} indicator criterion level in terms of its contribution to the disease status, n is the rank of this matrix. Fig. 2 provides the numerical ratings recommended for the verbal preferences expressed by the decision maker [6].

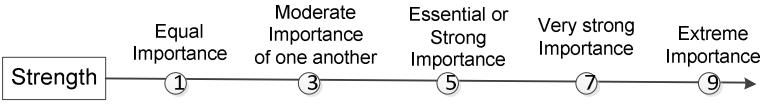

Fig. 2. Pairwise comparison scale for AHP preference

Once the pairwise comparison matrix has been established, the weight of each element being compared can be calculated. In this paper, we have used the logarithmic least square method in order to obtain the weights. The relative weight matrix B can be obtained by solving the following equations [6].

$$\min \sum_{i<j} \sum_{j=1}^{n} [\ln a_{ij} - \ln(\frac{w_i}{w_j})]^2 \tag{4}$$

$$\prod_{i=1}^{n} w_i = 1, \quad w_i > 0 \text{ for } i = 1,\ldots,n \tag{5}$$

Obtained eigenvector W of the hierarchy is as follows.

$$W=[0.1017, 0.2847, 0.2084, 0.2710, 0.1342]=[\text{FG, WR, HC, TR, BP}] \tag{6}$$

In order to check the consistency of the risk factor values in pairwise comparison matrix, a consistency ratio (C.R.) is used to determine the degree of consistency. If $C.R. \le 0.1$, it means that the consistency level is satisfactory. The C.R. and consistency index (C.I.) are defined as follows.

$$C.R. = C.I. / R.I. \tag{7}$$

$$C.I. = \frac{\lambda_{max} - n}{n-1} \tag{8}$$

where λ_{max} is the maximum eigenvalue of the pairwise comparison matrix. The random index (R.I.) is shown in Table 1 [6].

Table 1. Values of random index (R.I.) [6]

Matrix order (n)	1	2	3	4	5	6	7	8
Random index (R.I.)	0	0	0.58	0.9	1.12	1.24	1.32	1.41
Matrix order (n)	9	10	11	12	13	14	15	
Random index (R.I.)	1.45	1.49	1.51	1.48	1.56	1.57	1.59	

By substitute variable above by numerical value, the C.R. of the pairwise comparison matrix can be calculated as follows. Since C.R. is less than or equal 0.1, the consistency level is acceptable.

$$\lambda_{max}=5.00,\ n=5,\ \ C.I. = \frac{\lambda_{max} - n}{n-1} = \frac{5.00-5}{5-1} = 0 \tag{9}$$

$$C.R. = \frac{C.I.}{R.I.} = \frac{0}{1.12} = 0 \tag{10}$$

The computed weights and allocation of angle for medical tests indicators are shown in Table 2. From the table, we can observe that the examination results of waist/hip ratio, triglyceride, and HDL-cholesterol contribute the main factor of metabolic syndrome disease, which comply with the results of [10].

Table 2. Computed weights for each indicator and allocation of angle in radar chart

Examination Test Type	Weight (%)	Allocation of Angle (°)
Fasting Glucose (FG)	0.1017	36.612
Waist Circumference (WC)	0.2847	102.492
HDL Cholesterol (HC)	0.2084	75.024
Triglycerides (TR)	0.2710	97.56
Blood Pressure (BP)	0.1342	48.312

The circle of radar chart is marked off in accordance with the number of disease indicators and the weights calculated above. Some radiate lines are formed by the center of the circle and the marked point. These lines are regard as coordinate axis. Mark the data pretreated before on these coordinate axis and connect the marked points, then polygons for the values of disease indicators can be obtained. This is the radar chart of disease status for patient. Fig. 3 depicts a weighted radar chart using patient's sample medial test results. Table 3 shows the sample medical test results and characteristics of type 2 diabetes mellitus patient [8].

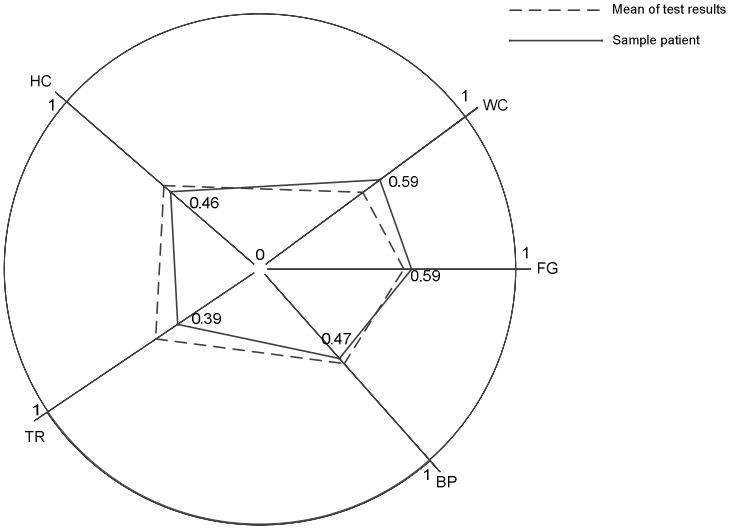

Fig. 3. Weighted radar chart of disease status

Table 3. Characteristics of type 2 diabetes mellitus patient

Examination Test Type	Sample Patient	Characteristics of diabetes mellitus patients (N=108)
Fasting Glucose (FG) (mg/dl)	90	176.4 ± 63.7
Waist Circumference (WC) (cm)	125.0	88.2 ± 5.5
HDL Cholesterol (HC) (mg/dl)	195.8	49.6 ± 13.5
Triglycerides (TR) (mg/dl)	48	163.9 ± 122.9
Blood Pressure (BP) (mmHg)	120	126.4 ± 15.2

3 Evaluation

According to [8], five risk factors of metabolic syndrome for Korean are defined as follows.

Table 4. Thresholds of five risk factors of metabolic syndrome for Korean

Examination Test Type	Thresholds
Fasting Glucose (FG) (mg/dl)	≥ 110mg/dl
Waist Circumference (WC) (cm)	≥ 90 (for man) ≥ 80 (for woman)
HDL Cholesterol (HC) (mg/dl)	< 40 (for man) < 50 (for woman)
Triglycerides (TR) (mg/dl)	≥ 150mg/dl
Blood Pressure (BP) (mmHg)	≥ 130/85

A patient is determined as having metabolic syndrome, if the patient's medical test results exceed the thresholds of risk factors in Table 4 with respect to three more risk factors. Therefore, by comparing the weighted radar chart of the patient with that of thresholds, it is possible to effectively determine whether the patient holds metabolic syndrome. Furthermore, by calculating the area of the two radar charts, we can compute the status of the patient's metabolic syndrome. Fig. 4 shows the two weighted radar charts of the patient and metabolic syndrome thresholds.

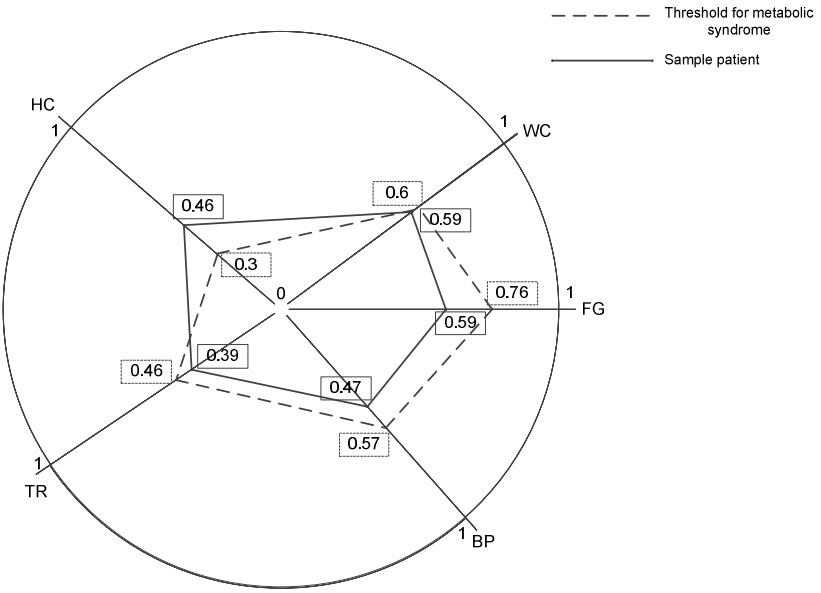

Fig. 4. Two weighted radar charts of the patient and metabolic syndrome thresholds

According to the test results, the patient is not determined as having a metabolic syndrome, because only two test results (fasting glucose and HDL cholesterol) exceeds the threshold. However, we can calculate the status of the patient having metabolic syndrome by comparing the overlapping area between two radar charts. In this example, we can compute the status of metabolic syndrome as 89.6% of metabolic syndrome thresholds.

4 Conclusions

It is known that the radar chart is a very useful method for qualitative data analysis despite of its weakness and useful for preliminarily diagnose patient' status of metabolic syndrome. So, in order to mitigate the known weakness, in this paper, we proposed an analytic hierarchy process based weighted radar chart scheme in order to effectively diagnose patients' chronic disease status, particularly the metabolic syndrome. Then, we presented the validity of the proposed scheme by using sample patient physiological data. Our evaluation results showed that the proposed scheme can be effectively used for medical decision process while physicians diagnose potential patients with metabolic syndrome.

Acknowledgment. This research was supported by the ICT Standardization program of MKE (The Ministry of Knowledge Economy).

References

1. Jeong, S., Youn, C., Shim, E., Kim, M., Cho, Y., Peng, L.: An Integrated Healthcare System for Personalized Chronic Disease Care in Home-Hospital Environments. IEEE Trans. Information Technology in Biomedicine 16(4), 572–585 (2012)
2. Koukias, V.G., et al.: A Personalized Framework for Medication Treatment Management in Chronic Care. IEEE Trans. Information Technology in Biomedicine 14(2), 464–472 (2010)
3. Dahlstorm, O., Timpka, T., Hass, U., Skogh, T., Thyberg, I.: A Simple Method for Heuristic Modeling of Expert Knowledge in Chronic Disease: Identification of Prognostic Subgroups in Rheumatology. In: 21st International Congress of the European Federation for Medical Informatics, pp. 157–162 (2008)
4. Schutz, H., Speckesser, S., Schmid, G.: Benchmarking labour market performance and labour market policies: theoretical foundations and applications. Discussion paper, No. FS I 98-205 (1998), http://hdl.handle.net/10419/43918
5. Schmid, G., Schutz, H., Speckesser, S.: Broadening the Scope of Benchmarking: Radar Charts and Employment Systems. Labor. 13(4), 879–899 (1999)
6. Saaty, T.L.: The Analytic Hierarchy Process. McGraw-Hill, New York (1980)
7. Li, X., Hong, W., Wang, J., Song, J., Kang, J.: Research on the Radar Chart Theory Applied to the Indoor Environmental Comfort Level Evaluation. In: 6th World Congress on Intelligent Control and Automation, pp. 5214–5217 (2006)
8. Kim, H.: Differences in Prevalence and Risk Factors of the Metabolic Syndrome by Gender in Type 2 Diabetic Patients. Korean Journal of Adult Nursing 18(1), 3–9 (2006)
9. Yijing, L., Ming, L.: Evaluation of Drawing Ability Based on Radar Chart. In: International Conference on Information Technology and Computer Science, pp. 574–576 (2009)
10. Shen, B., Todaro, J., Niaura, R., McCaffery, J., Zhang, J., Spiro, A., Ward, K.: Are Metabolic Risk Factors One Unified Syndrome? Modeling the Structure of the Metabolic Syndrome X. American Journal of Epidemiology 157(8), 701–711 (2003)