International Journal of Innovative Computing, Information and Control
Volume **8**, Number **10(B)**, October **2012**

ICIC International ©2012 ISSN 1349-4198
pp. **7133–7142**

SENSITIVITY OF AN INTERVIEW CHART FOR MEDICAL DIAGNOSES OF PRIMARY HEADACHES

Jürgen Symanzik[1], Kyung Ho Choi[2], Gil Seong Mun[3] and Jeong Yong Ahn[3,*]

[1]Department of Mathematics and Statistics
Utah State University
3900 Old Main Hill, Logan, Utah 84322-3900, USA
symanzik@math.usu.edu

[2]College of Alternative Medicine
Jeonju University
45 Baengma-gil, Jeonju, Jeonbuk 560-759, Korea
chk414@jj.ac.kr

[3]Department of Statistics (Institute of Applied Statistics)
Chonbuk National University
567 Baekje-daero, Jeonju, Jeonbuk 561-756, Korea
rightway@jbnu.ac.kr; *Corresponding author: jyahn@jbnu.ac.kr

Received August 2011; revised December 2011

Abstract. *In this study, we introduce an interview chart to aid with the medical diagnosis of primary headaches and a diagnosis method based on the chart. In addition, we present sensitivity analysis results to show the reliability of medical diagnoses using the interview chart. We show that a diagnosis using the interview chart is fairly stable by conducting simulations based on small changes of the interview chart.*
Keywords: Diagnosis measure, Interview chart, Medical diagnosis, Prediction model, Sensitivity analysis

1. **Introduction.** Since Zadeh [15] introduced the concept of fuzzy sets (FS), they have been applied to various fields. In medical science, the FS framework can be utilized in several different approaches to modeling the diagnostic process. An application of FS on medical science fields already proposed by Zadeh [16], and Sanchez [11] invented a fully developed relationships modelling theory of symptoms and diseases using FS. Later, Atanassov [4] introduced the concept of intuitionistic fuzzy set (IFS) and FS theory has been utilized in many approaches to model the diagnostic process. De et al. [9] applied the max-min-max composition rule to determine the disease of patients as an application of the Sanchez's approach. Szmidt and Kacprzyk [12] indicated the drawbacks of the diagnosis method based on the max-min-max composition rule, and proposed a diagnosis approach based on the distances between diseases and symptoms. Chetia and Das [8] extended the approaches for medical diagnosis using interval-valued fuzzy soft sets.

Most of these studies proposed the diagnosis method and presented trivial examples using simple fuzzy data sets. However, they have not addressed the reliability of the data used for the diagnosis process. The information is an important factor in medical diagnosis because the sensitivity of data can directly affect the results.

In this paper, we explore the sensitivity analysis of the data used for a medical diagnosis. The goal of this study is not to propose a method for medical diagnosis but rather to show the reliability of a data set used in the diagnosis process. We at first introduce

a method for medical diagnosis based on the interview chart with interval-valued fuzzy data developed in our previous works [2, 3], and then present simulation results that can explore the sensitivity of the method. The features and mail contributions of this study are as follows: we presented an example of the simulation study for medical diagnosis based on the relation of the symptoms and diseases. Simulation studies are increasingly being used in the medical literature for a wide variety of situations recently [6]. Second, we showed the reliability of medical diagnosis based on the interview chart. As the results of the sensitivity analysis, the diagnosis method is fairly stable and therefore, we expect the approach using the interview chart can be applied in practice. Third, we fitted a regression model to statistically predict the changes of the diagnosis result. With the model, we can figure out the relationship between the predicted coincidence and the number of symptoms and small changes.

In Section 2 of this paper, we briefly review an interview chart to aid with the medical diagnosis of primary headaches. In addition, we summarize a diagnosis method based on the interview chart. In Section 3, we present our sensitivity analysis results to show the reliability of diagnoses using the interview chart. We also present a prediction model of the diagnosis based on the number of symptoms and the number of small changes in the symptoms. We finish with a brief conclusion in Section 4.

2. **Preliminaries.**

2.1. **Interview chart.**

In medical science, a diagnosis can be regarded as a label assigned by the physician to describe and synthesize the medical status of a patient. It is based on the information about the patient collected by the physician, his/her knowledge of medical science, and other investigative procedures such as computer tomography (CT) or magnetic resonance imaging (MRI). Likewise, the critical first steps for the diagnosis of a headache are to take a detailed patient history, a focused physical examination, and a focused neurological examination. The detailed history includes characteristics of the headache, assessment of the functional impairment, past medical history, family history, current medications, previous medications for headaches, and so on. Many parts of these histories are collected via interviews. Therefore, a screening method using questionaires is helpful in medical diagnosis and the interview chart is a leading part of headache diagnoses [5].

In our earlier work [1], we developed an interview chart for the preliminary diagnosis of headaches, where the qualitative data from the interview chart was obtained and then quantified by dual scaling. In the next study [2], an extended version of our previous interview chart was implemented. In the chart, we reformed the fuzzy degrees and added some composite symptoms.

In a recent study [3], we developed an interval-valued intuitionistic fuzzy sets (IV-IFS) version of the interview chart developed in our previous studies, based on physician knowledge. In the chart, each item has confirmability degrees of membership and non-membership with the relation among symptoms and the three diseases. The degree of membership, M, indicates the degree to which symptom s confirms the presence of disease d. The degree of non-membership, N, indicates the degree to which symptom s does not confirm the presence of disease d.

2.2. **A diagnosis method.**

In this section, we summarize an approach for the medical diagnosis of three headache types (migraine, tension and cluster) originally proposed in Ahn et al. [3]. This approach is divided into four stages:

- Stage 1: Collect the patient's degrees and confirmability degrees of the patient's symptoms. Confirmability degrees, the relationship between symptoms and diseases,

are presented in the interview chart. Patient's degrees, the relationship between patient and symptoms, are assigned by a physician. In other words, confirmability degrees represent the general relationship between symptoms and diseases, and patient's degrees represent a particular relationship between a patient and symptoms.

- Stage 2: Calculate the interval-valued intuitionistic fuzzy weighted arithmetic average (IIFWAA) of the patient's degrees and confirmability degrees, respectively, using the aggregate operator of Definition 2.1. A disease in general is presented through many symptoms and the symptoms significantly associated with the disease. Therefore, it is necessary to aggregate the symptoms. Aggregation of intuitionistic fuzzy information has attracted considerable interest from researchers in recent years [13].
- Stage 3: Calculate the distance between interval-valued intuitionistic fuzzy sets using the distance measure of Definition 2.2 and the IIFWAA calculated in Stage 2.
- Stage 4: Determine the disease of the patient, based on the distance. The lowest distance indicates the most appropriate diagnosis.

Definition 2.1. ***(IIFWAA Operator)*** *Let* $A = \{< x_i, M_A(x_i), N_A(x_i) >| \ i = 1, 2, \ldots, n\}$ *be a collection of interval-valued intuitionistic fuzzy values. Then, an IIFWAA operator is defined as follows:*

$$IIFWAA(A) = ([1 - \Pi_{i=1}^{n}(1 - M_{AL}(x_i))^{\omega_i},\ 1 - \Pi_{i=1}^{n}(1 - M_{AU}(x_i))^{\omega_i}],$$
$$[\Pi_{i=1}^{n}(N_{AL}(x_i))^{\omega_i},\ \Pi_{i=1}^{n}(N_{AU}(x_i))^{\omega_i}])$$

where n *is the number of fuzzy data,* $M_A(x_i)$ *is an interval value* $(M_{AL}(x_i), M_{AU}(x_i))$, $N_A(x_i)$ *is* $(N_{AL}(x_i), N_{AU}(x_i))$, x_i *is the* i^{th} *fuzzy data with* $M_A(x_i)$ *and* $N_A(x_i)$, $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ *are the weight vectors of* A. *In addition,* $\omega_i > 0$ *and* $\sum_{i=1}^{n} \omega_i = 1$. *In this study, we use* $\omega = (1/n, 1/n, \ldots, 1/n)$.

Definition 2.2. ***(Distance Measure)*** *For any two interval-valued intuitionistic fuzzy sets* $A = \{< x_i, M_A(x_i),\ N_A(x_i) >| \ i = 1, 2, \ldots, n\}$ *and* $B = \{< x_i, M_B(x_i), N_B(x_i) >| \ i = 1, 2, \ldots, n\}$, *the normalized Hamming distance considering the hesitate part is defined as follows:*

$$l_h(A, B) = (1/4n) \sum [\ |M_{AL}(x_i) - M_{BL}(x_i)| + |M_{AU}(x_i) - M_{BU}(x_i)|$$
$$+|N_{AL}(x_i) - N_{BL}(x_i)| + |N_{AU}(x_i) - N_{BU}(x_i)|$$
$$+|H_{AL}(x_i) - H_{BL}(x_i)| + |H_{AU}(x_i) - H_{BU}(x_i)|\ ]$$

where H *is the degree of indeterminacy (hesitation part), i.e.,* $H_{AL}(x_i) = 1 - (M_{AL}(x_i) + N_{AL}(x_i))$ *and* $H_{AU}(x_i) = 1 - (M_{AU}(x_i) + N_{AU}(x_i))$.

Example 2.1. *Let us assume that a patient* P_1 *has the following symptoms* (M5, M12) *of migraine,* (T5, T13, T16) *of tension headache, and* (C5, C13) *of cluster headache. The stages for the medical diagnosis, based on our proposed approach, are as follows:*

- *Stage 1: First, we collect the patient's degrees and confirmability degrees. Table 1 shows the patient's degrees assigned by a physician and Table 2 shows the confirmability degrees indicated in the interview chart.*
- *Stage 2: Based on Table 1 and Table 2, Table 3 and Table 4 are calculated by applying the IIFWAA operator.*
- *Stage 3: Table 5, the distance between interval-valued intuitionistic fuzzy sets, is calculated by applying the distance measure to the data from Table 3 and Table 4.*
- *Stage 4: We can preliminarily diagnose that patient* P_1 *suffers most likely from tension headache. Additional diagnostic investigations may be considered for a more accurate diagnosis, given that the Hamming distance* l_h *for migraine is only slightly*

bigger than for tension headache as shown in Table 5. Therefore, migraine and tension headache might both be reasonable diagnoses for patient P_1.

3. **Sensitivity Analysis.** Sensitivity analysis estimates the rate of change in the output of a model, which is caused by small changes in the model inputs. Sensitivity analysis is hence considered by some researchers as a prerequisite for model building in any setting, be it diagnostic or prognostic, and in any field where models are used [10]. It has been applied in various fields including complex engineering systems, economics, physics, social sciences, medical decision making, risk assessment and many others [7, 14].

Example 3.1 is an extension of Example 2.1 with just one small change. We will show the change in the output caused by one small change of the input.

Example 3.1. *A patient P_1's symptoms are* (M5, M12, T5, T13, T16, C5, C13).

- *Stage 1: First, we collect the patient's degrees and confirmability degrees. Table 6 shows the patient's degrees assigned by a physician. Table 7 shows the confirmability degrees with just one small change in the symptom $M12$.*
- *Stage 2: Likewise to Example 2.1, Table 8 and Table 9 are calculated by applying the IIFWAA operator.*
- *Stage 3: Table 10 shows the distance between interval-valued intuitionistic fuzzy sets.*

TABLE 1. Patient P_1's degrees

symptom	M5	M12	T5	T13	T16	C5	C13
M	[0.5, 0.6]	[0.7, 0.8]	[0.4, 0.5]	[0.7, 0.8]	[0.6, 0.7]	[0.5, 0.6]	[0.6, 0.7]
N	[0.1, 0.3]	[0.0, 0.1]	[0.2, 0.3]	[0.0, 0.1]	[0.1, 0.2]	[0.2, 0.3]	[0.2, 0.3]

TABLE 2. P_1's confirmability degrees

	Migraine		Tension		Cluster	
symptom	M	N	M	N	M	N
M5	[0.5, 0.6]	[0.2, 0.3]	[0.4, 0.5]	[0.3, 0.4]	[0.3, 0.5]	[0.3, 0.4]
M12	[0.6, 0.7]	[0.1, 0.2]	[0.2, 0.3]	[0.5, 0.6]	[0.1, 0.3]	[0.4, 0.6]
T5	[0.3, 0.4]	[0.5, 0.6]	[0.6, 0.7]	[0.1, 0.2]	[0.2, 0.3]	[0.6, 0.7]
T13	[0.1, 0.3]	[0.5, 0.6]	[0.6, 0.7]	[0.1, 0.2]	[0.0, 0.1]	[0.6, 0.8]
T16	[0.2, 0.3]	[0.5, 0.6]	[0.7, 0.8]	[0.0, 0.1]	[0.1, 0.2]	[0.6, 0.7]
C5	[0.2, 0.3]	[0.5, 0.6]	[0.0, 0.1]	[0.6, 0.7]	[0.7, 0.8]	[0.1, 0.2]
C13	[0.3, 0.4]	[0.3, 0.4]	[0.2, 0.3]	[0.3, 0.5]	[0.4, 0.6]	[0.1, 0.3]

TABLE 3. IIFWAA of the patient P_1's degrees

	symptom M	symptom T	symptom C
P_1	([0.61, 0.72], [0.00, 0.17])	([0.58, 0.69], [0.00, 0.18])	([0.55, 0.65], [0.20, 0.30])

TABLE 4. IIFWAA of the P_1's confirmability degrees

	Migraine	Tension	Cluster
symptom M	([0.55, 0.65], [0.14, 0.24])	([0.20, 0.34], [0.50, 0.60])	([0.25, 0.35], [0.39, 0.49])
symptom T	([0.31, 0.41], [0.39, 0.49])	([0.64, 0.74], [0.00, 0.16])	([0.11, 0.21], [0.42, 0.59])
symptom C	([0.21, 0.41], [0.35, 0.49])	([0.10, 0.20], [0.60, 0.73])	([0.58, 0.72], [0.10, 0.24])

TABLE 5. Distance for P_1's symptoms: l_h

T	Migraine	Tension	Cluster
P_1	0.289	0.283	0.339

TABLE 6. Patient P_1's degrees, identical to patient's degree shown in Table 1

symptom	M5	M12	T5	T13	T16	C5	C13
M	[0.5, 0.6]	[0.7, 0.8]	[0.4, 0.5]	[0.7, 0.8]	[0.6, 0.7]	[0.5, 0.6]	[0.6, 0.7]
N	[0.1, 0.3]	[0.0, 0.1]	[0.2, 0.3]	[0.0, 0.1]	[0.1, 0.2]	[0.2, 0.3]	[0.2, 0.3]

TABLE 7. P_1's confirmability degrees, almost identical to patient's degree shown in Table 2, except the degrees of migraine for M12

	Migraine		Tension		Cluster	
symptom	M	N	M	N	M	N
M5	[0.5, 0.6]	[0.2, 0.3]	[0.4, 0.5]	[0.3, 0.4]	[0.3, 0.5]	[0.3, 0.4]
M12	[0.67, 0.77]	[0.03, 0.13]	[0.2, 0.3]	[0.5, 0.6]	[0.1, 0.3]	[0.4, 0.6]
T5	[0.3, 0.4]	[0.5, 0.6]	[0.6, 0.7]	[0.1, 0.2]	[0.2, 0.3]	[0.6, 0.7]
T13	[0.1, 0.3]	[0.5, 0.6]	[0.6, 0.7]	[0.1, 0.2]	[0.0, 0.1]	[0.6, 0.8]
T16	[0.2, 0.3]	[0.5, 0.6]	[0.7, 0.8]	[0.0, 0.1]	[0.1, 0.2]	[0.6, 0.7]
C5	[0.2, 0.3]	[0.5, 0.6]	[0.0, 0.1]	[0.6, 0.7]	[0.7, 0.8]	[0.1, 0.2]
C13	[0.3, 0.4]	[0.3, 0.4]	[0.2, 0.3]	[0.3, 0.5]	[0.4, 0.6]	[0.1, 0.3]

TABLE 8. IIFWAA of the patient P_1's degrees, identical to Table 3

	symptom M	symptom T	symptom C
P_1	([0.61, 0.72], [0.00, 0.17])	([0.58, 0.69], [0.00, 0.18])	([0.55, 0.65], [0.20, 0.30])

- *Stage 4: As a result, we can preliminarily diagnose that patient P_1 suffers most likely from migraine. Thus, just one small change in the confirmability degrees leads to a different preliminary diagnosis here.*

3.1. **Simulation environment.** Simulation is performed in IBM-PC including Pentium processor 2.10 GHz and 2 GB main memory. The program for simulation was written in Java language, and the simulation takes about 15.5 hours to complete.

Table 11 shows the parameters used in the simulation. The parameters n_1 and n_2 present the number of patients and simulation runs. The parameter s presents the number of symptoms, and sc is the number of small changes. In this study, small changes are carried out at random in the confirmability degrees of the interview chart because the goal is to show the reliability of the interview chart. When a patient has 7 symptoms, for example, the confirmability degrees with membership and non-membership value are 21 ($= 7_{symptoms} \times 3_{types\ of\ headaches}$) as shown in Table 2. We, therefore, can make up to 21 small changes.

The range for each small change has been limited to values between 0 and 0.1. For example, if M_U increases by 0.05 then N_U decreases by 0.05. Likewise, if M_U decreases by 0.05, then N_U increases by 0.05. In our previous Example 3.1, one small change of magnitude 0.07 occurred for symptom M12 and migraine, increasing M from $[0.6, 0.7]$ to $[0.67, 0.77]$ and decreasing N from $[0.1, 0.2]$ to $[0.03, 0.13]$ as shown on Table 2 and Table

TABLE 9. IIFWAA of the P_1's confirmability degrees, almost identical to Table 4, except a small change for symptom M for migraine

	Migraine	Tension	Cluster
symptom M	([0.59, 0.70], [0.08, 0.20])	([0.20, 0.34], [0.50, 0.60])	([0.25, 0.35], [0.39, 0.49])
symptom T	([0.31, 0.41], [0.39, 0.49])	([0.64, 0.74], [0.00, 0.16])	([0.11, 0.21], [0.42, 0.59])
symptom C	([0.21, 0.41], [0.35, 0.49])	([0.10, 0.20], [0.60, 0.73])	([0.58, 0.72], [0.10, 0.24])

TABLE 10. Distance for P_1's symptoms: l_h, almost identical to Table 5, except that the Hamming distance l_h for migraine now is slightly smaller than for tension headache

T	Migraine	Tension	Cluster
P_1	0.270	0.283	0.339

TABLE 11. Simulation parameters

Parameters	Meaning	Value
n_1	the number of patients	500
n_2	the number of simulation runs	$10,000$
sc	the number of small changes	$1 \sim 20$
s	the number of symptoms	$7 \sim 15$
small changes	changes in the degrees of the interview chart	$0 \sim 0.1$

7. In addition, we check that M_L and N_L are not less than 0.0. Therefore, the inequalities $M_U + N_U \leq 1.0$, $M_L \geq 0.0$ and $N_L \geq 0.0$ are satisfied.

The patient data such as Table 1 are simulated from conditions that occurred in medical practice during our research. In general, physicians should assign values above 0.3 as a patient's membership degree M for symptoms that are present in this patient. Based on this additional information, we randomly generate the patient degrees.

3.2. **Simulation results.** In this section, we present simulation results of the sensitivity to show the reliability of the medical diagnosis using the interview chart. Table 12 shows a part of the simulation results. The numbers in the cells represent the coincidence of the diagnosis resulting in small changes. The first value of Table 12, 0.948, is the coincidence of the diagnosis result with one small change when a patient has seven symptoms. Likewise, the value 0.778 is the coincidence of the diagnosis result with 20 small changes when a patient has seven symptoms.

Figure 1 shows a plot of the simulation results. The diagnosis results show a slight decrease of coincidence when the number of small changes increases. The average of the coincidence gets close to 0.84 when 20 small changes occur. The simulation results, therefore, show that the resulting diagnosis using the interview chart is fairly stable.

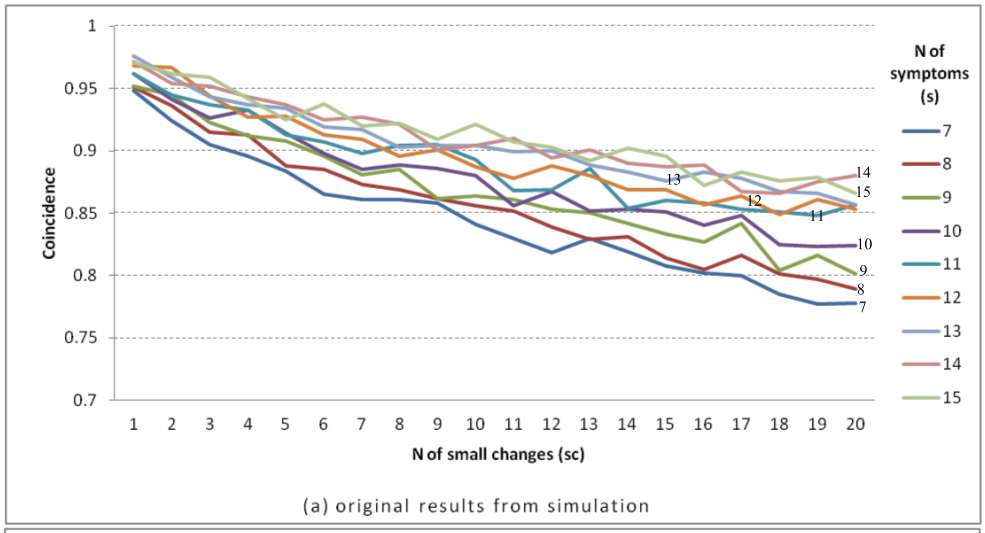
To statistically predict the changes of the diagnosis results, we fit a multiple quadratic regression model to the simulation data. A possible model is

$$\hat{y} = 0.8 + 0.022s - 0.001s^2 - 0.011sc + 0.0002sc^2$$

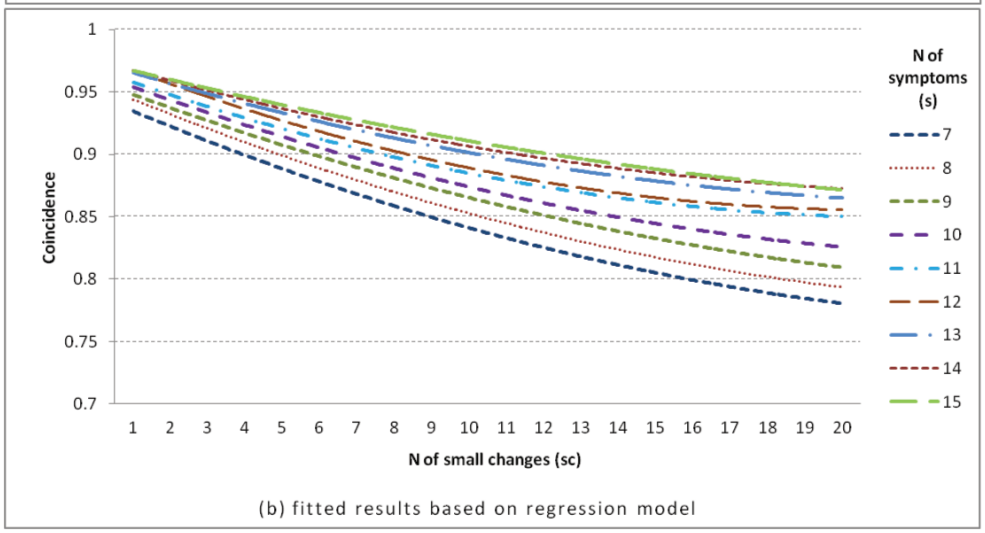
where $\hat{y}$ is the predicted coincidence, s is the number of symptoms, and sc is the number of small changes. This model had a coefficient of determination $R^2 = 0.955$ and a standard error of estimate $s_e = 0.010$.

TABLE 12. Simulation results. For selected combinations of the number of small changes (sc) and the number of symptoms (s), the coincidence of the diagnosis result with sc small changes when a patient has s symptoms, is indicated.

		N of small changes (sc)						
		1	3	5	7	10	15	20
N of symptoms (s)	7	0.948	0.905	0.884	0.861	0.841	0.808	0.778
	8	0.951	0.915	0.888	0.873	0.856	0.814	0.789
	9	0.952	0.923	0.908	0.881	0.864	0.833	0.801
	10	0.962	0.926	0.914	0.885	0.880	0.851	0.824
	11	0.962	0.937	0.913	0.898	0.893	0.860	0.857
	12	0.968	0.944	0.928	0.909	0.887	0.869	0.853
	13	0.976	0.943	0.934	0.917	0.904	0.876	0.857
	14	0.972	0.952	0.937	0.927	0.904	0.887	0.880
	15	0.971	0.959	0.925	0.920	0.921	0.896	0.866



(a) original results from simulation



(b) fitted results based on regression model

FIGURE 1. Graphical summary of the simulation results

3.3. **A practical example.** In this section, we will present the reliability of the data set (interview chart) used in medical diagnosis through an example. The example will show no change in the output even though there are 20 small changes in the input.

TABLE 13. Patient P_2's degrees

symptom	M10	M22	M23	T7	C2	C9	C11
M	[0.4, 0.6]	[0.6, 0.7]	[0.4, 0.5]	[0.4, 0.5]	[0.4, 0.5]	[0.6, 0.7]	[0.4, 0.5]
N	[0.2, 0.3]	[0.2, 0.3]	[0.1, 0.2]	[0.1, 0.3]	[0.1, 0.3]	[0.2, 0.3]	[0.2, 0.3]

TABLE 14. P_2's confirmability degrees

	Migraine		Tension		Cluster	
symptom	M	N	M	N	M	N
M10	[0.5, 0.6]	[0.1, 0.3]	[0.3, 0.4]	[0.4, 0.5]	[0.4, 0.5]	[0.1, 0.3]
M22	[0.7, 0.8]	[0.1, 0.2]	[0.1, 0.2]	[0.6, 0.8]	[0.1, 0.2]	[0.7, 0.8]
M23	[0.7, 0.8]	[0.1, 0.2]	[0.1, 0.2]	[0.6, 0.7]	[0.2, 0.3]	[0.6, 0.7]
T7	[0.2, 0.3]	[0.5, 0.6]	[0.5, 0.6]	[0.2, 0.3]	[0.3, 0.4]	[0.4, 0.5]
C2	[0.4, 0.5]	[0.3, 0.5]	[0.2, 0.3]	[0.4, 0.5]	[0.6, 0.7]	[0.2, 0.3]
C9	[0.5, 0.6]	[0.2, 0.4]	[0.3, 0.4]	[0.2, 0.3]	[0.6, 0.7]	[0.1, 0.3]
C11	[0.2, 0.4]	[0.3, 0.5]	[0.3, 0.4]	[0.2, 0.3]	[0.5, 0.7]	[0.1, 0.3]

TABLE 15. IIFWAA of the patient P_2's degrees

	symptom M	symptom T	symptom C
P_1	([0.48, 0.61], [0.16, 0.26])	([0.40, 0.50], [0.10, 0.30])	([0.48, 0.58], [0.16, 0.30])

TABLE 16. IIFWAA of the P_2's confirmability degrees

	Migraine	Tension	Cluster
symptom M	([0.64, 0.75], [0.10, 0.23])	([0.17, 0.27], [0.52, 0.65])	([0.24, 0.35], [0.35, 0.55])
symptom T	([0.20, 0.30], [0.50, 0.60])	([0.50, 0.60], [0.20, 0.30])	([0.30, 0.40], [0.40, 0.50])
symptom C	([0.38, 0.51], [0.26, 0.46])	([0.27, 0.37], [0.25, 0.36])	([0.57, 0.70], [0.13, 0.30])

Let us consider patient P_2. P_2's symptoms are (M10, M22, M23, T7, C2, C9, C11). Table 13 shows the patient P_2's degrees and Table 14 shows the confirmability degrees. Table 15 and Table 16 are calculated by applying the IIFWAA operator. Table 17 is the Hamming distance. We can preliminarily diagnose that patient P_2 suffers most likely from cluster headache.

Table 18 shows the P_2's confirmability degrees with 20 small changes in Table 14. Likewise to Examples 2.1 and 3.1, Table 19 is calculated by applying the distance measure of Definition 2.2, and we have the same result even after 20 small changes.

4. **Conclusion.** In this paper, we introduced an improved interview chart to aid with the medical diagnosis of primary headaches. The main part of this paper contains a simulation study to determine the effect of small changes on the diagnosis outcome. The results of the simulation study show that the diagnosis using the interview chart is fairly stable even if numerous small changes occur. We, therefore, expect that an approach using an interview chart can be applied in practice as a preliminary diagnosis tool for headaches.

This study has some remaining problems for future explorations. First, the symptoms of patients are assigned at random for simulation in this study. To obtain precise results, there needs to be a practical comparison between simulation results and the results based on real data. Second, in most cases, even multiple small changes in the confirmability

TABLE 17. Distance for P_2's symptoms: l_h

T	Migraine	Tension	Cluster
P_2	0.213	0.246	0.206

TABLE 18. P_2's confirmability degrees, 20 small changes to patient's degree shown in Table 14, except the degrees of tension for C11

	Migraine		Tension		Cluster	
symptom	M	N	M	N	M	N
M10	[0.55, 0.65]	[0.05, 0.25]	[0.20, 0.30]	[0.50, 0.60]	[0.43, 0.53]	[0.07, 0.27]
M22	[0.76, 0.86]	[0.04, 0.14]	[0.20, 0.30]	[0.50, 0.70]	[0.18, 0.28]	[0.62, 0.72]
M23	[0.78, 0.88]	[0.02, 0.12]	[0.07, 0.17]	[0.63, 0.73]	[0.28, 0.38]	[0.52, 0.62]
T7	[0.18, 0.28]	[0.52, 0.62]	[0.42, 0.52]	[0.28, 0.38]	[0.40, 0.50]	[0.30, 0.40]
C2	[0.30, 0.40]	[0.40, 0.60]	[0.18, 0.28]	[0.42, 0.52]	[0.67, 0.77]	[0.13, 0.23]
C9	[0.41, 0.51]	[0.29, 0.49]	[0.23, 0.33]	[0.27, 0.37]	[0.67, 0.77]	[0.03, 0.23]
C11	[0.12, 0.32]	[0.38, 0.58]	[0.3, 0.4]	[0.2, 0.3]	[0.56, 0.76]	[0.04, 0.24]

TABLE 19. Distance for P_2's symptoms: l_h, after 20 small changes

T	Migraine	Tension	Cluster
P_2	0.273	0.262	0.175

degrees will not lead to a different diagnosis. However, as seen in Examples 2.1 and 3.1, in the case of two (or three) almost identical Hamming distances l_h, just one small change may result in a different diagnosis. We should investigate how we can assign fuzzy diagnoses because both migraine and tension headaches would be listed as almost identically plausible diagnoses in Examples 2.1 and 3.1. Lastly, it also requires some researches on the characteristics of the Hamming distance produced from this study.

Acknowledgment. This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2011-0008954).

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