Intelligent Ontological Multi-Agent for Healthy Diet Planning

Mei-Hui Wang, Chang-Shing Lee, Kuang-Liang Hsieh, Chin-Yuan Hsu, and Chong-Ching Chang

***Abstract*—Good eating habits can make human beings to live in a healthy lifestyle. When a person constantly eats too much or too little, it will have a high risk of causing a disease for him. Therefore, developing healthy and balanced eating habits is important for most people to stay away from diseases. This study proposes an intelligent healthy diet planning multi-agent (IHDPMA), including a personal profile agent, a nutrition facts analysis agent, a knowledge analysis agent, a discovery agent, a fuzzy inference agent, and a semantic generation agent for healthy diet planning. The IHDPMA provides a semantic analysis of healthy diet status for people based on the pre-constructed ontology by domains experts and results of fuzzy inference. With the generated semantic analysis, people can get healthy information about what they eat and make it easier to eat a balanced and healthy diet. The experimental platform has been constructed to test the performance of the IHDPMA. The results indicate that the IHDPMA can effectively work for healthy diet planning.**

I. Introduction

Nowadays, people can choose many kinds of food so that they have a higher risk of developing diseases if they are lack of the healthy eating habits. Therefore, an intelligent agent for healthy diet planning is becoming more and more important research topic. The agent technology is a key area in the field of artificial intelligence research [5]. The functionality of an intelligent agent covers six attributes, including autonomy, continuity, adaptivity, goal orientation, learning ability, and communication [2]. In addition, the intelligent agent system is applied to many research domains. For example, Sanchez *et al.* [1] presented the Semantic Web services and Multi-Agent Systems framework (SEMMAS) to provide a seamless integration of the technologies by making use of ontologies to facilitate the interoperation among agents and Web services. Chang [2] investigated the employment of the intelligent agents in a web-based auction process. Because of monotonous and uninteresting, Zunino and Campo [3] proposed a multi-agent system called Chronos for assisting users in organizing their meetings. Wang *et al.* [4] proposed an agent-mediated, constraint-based decision and coordination approach to supply chain integration in a web-based environment.

Ontology has become a very powerful way of representing the information and its semantics [11]. For example, Lee *et al.* [10] proposed a fuzzy ontology to apply for news summarization. Reformat and Ly [11] proposed an ontology-based approach to provide a rich environment for expressing different types of information including perceptions [11]. Multi-agent systems along with ontologies have been applied for supporting distributed decision making in several fields such as manufacturing, business, and engineering [5]. For example, Chen *et al.* [5] developed a conceptual framework to create a virtual observatory with semantically enriched Web services. Debenham and Sierra [6] proposed an agent's communication language to structure the dialogues and process the information gathered by the agents. Lee *et al.* [7] presented a meeting scheduling system by combing a genetic fuzzy agent with an ontology model. Applying agent technology to healthcare is also an important research topic. For example, Lee and Wang presented an ontology-based intelligent agent to recognize the respiratory waveform [8] and an ontological fuzzy agent to apply for electrocardiogram (ECG) [9]. The GruSMA team [13] designed and implemented the Health Care Services multi-agent system to help doctors make fewer errors by reminding them at each point in diagnosis and treatment.

This study presents an intelligent multi-agent for healthy diet planning. First, the domain experts use the protege developed by the Stanford Center for Biomedical Informatics Research [15] to pre-define the food ontology according to the collected food's nutrition facts from the Internet and convenient stores in Taiwan. Then, a Fuzzy Markup Language (FML), proposed by Acampora and Loia [12], is adopted to model the necessary knowledge base and rule base of the fuzzy inference. Next, the proposed intelligent healthy diet planning multi-agent (IHDPMA), including a *personal profile agent*, a *nutrition facts analysis agent*, a *knowledge analysis agent*, a *discovery agent*, a *fuzzy inference agent*, and a *semantic generation agent*, can help people deal with healthy diet planning. Based on the food ontology, knowledge base, and rule base, each agent executes different kinds of functions to detect the semantics of the healthy diet status. Finally, the results of the healthy diet status are stored into the healthy diet status repository. The remainder of this paper is structured as follows: Section II describes the system structure and the diet ontology for the healthy diet planning. Section III introduces the details of the proposed intelligent multi-agent. The experimental results are shown in Section IV and the conclusions are finally given in Section V.

II. System Structure and Diet Ontology

In this section, the system structure of the IHDPMA and the diet ontology are presented. Additionally, the FML is also briefly described in this section.

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A. System Structure

Fig. 1 shows the architecture of the IHDPMA platform. It is composed of three layers, including a *knowledge layer*, a *communication layer*, and an *application layer*. The *knowledge layer* includes the knowledge base, the rule base, the profile ontology, the food ontology, and the healthy diet status repository. The *communication layer* is designed to offer some application interfaces, such as FML, web ontology language (OWL), and healthy diet status, to interact between the *application layer* and the *knowledge layer*. First, the user with a personal digital assistant (PDA), a personal computer, or a notebook utilizes the IHDPMA platform through the Internet. After successful authentication, the user can deal with the personal meal based on the knowledge stored in the *knowledge layer* and then perform the analysis of the healthy diet status through the *communication layer*.

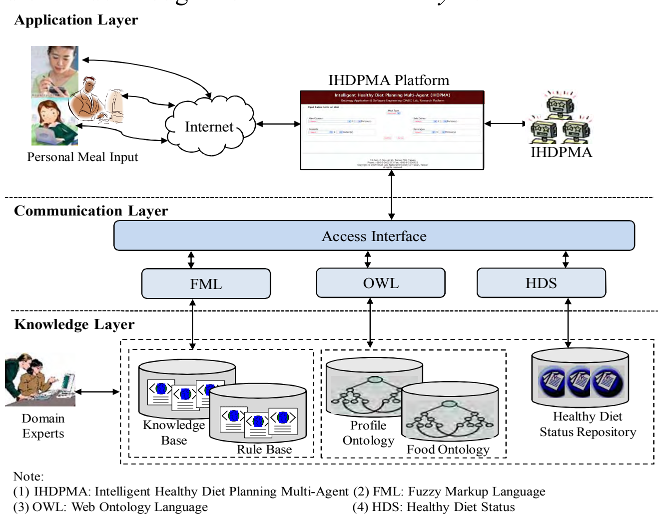

Fig. 1. IHDPMA platform architecture.

B. Ontology Model

Based on the levels of organization [14] and our previous work [10], this study presents a novel structure of the domain ontology, including a *domain layer*, a *category layer*, and a *concept layer* shown in Fig. 2. An aggregation of elements in a lower layer is a component in a higher layer [14]. The *domain layer* represents the domain name of the ontology. The *category layer* defines several categories, labeled as "category *1*, category *2*, category *3*, …, and category *k*". Each concept in the *concept layer*, contains a concept name C_i and an attribute set $\{A_{C_i1},\cdots,A_{C_iq_i}\}$, for an application domain. Based on the structure of the domain ontology, we apply it to the food ontology, shown in Fig. 3. However, the *concept layer* is composed of two sub-layers, namely the *item sub-layer* and the *nutrition facts sub-layer*. The domain name of this ontology is "*meal*." The categories in the *category layer* include "*Main Courses*," "*Side Dishes*," "*Desserts*," and "*Beverages*." Each concept in the *item sub-layer* represents a food item and similar food items are grouped together in a dotted circle. For example, "*Citizen Lunch Box*" and "*Hawaii Pizza*" are one of "*Main Courses*" category. "*Coca Cola*" and "*Apple Juice*" are grouped into the "*Beverages*" category. According to the nutrition facts label of each food product [16], the nutrition facts contain product-specific information such as serving size, calories, and nutrient information as well as a footnote with Daily Values (DVs) based on a 2000 calorie diet. In this study, the calories per portion and the grams of carbohydrate, protein, and fat per portion are considered in the construction of the food ontology. Therefore, in the *nutrient facts sub-layer*, each concept contains product-specific information such as "calories" and "nutrient information (carbohydrate, protein, and fat)." For instance, the nutrition facts for each portion of the "*Egg Pudding*" are 236kcal and the grams of carbohydrate, protein, and fat are 17g, 6g, and 16g, respectively.

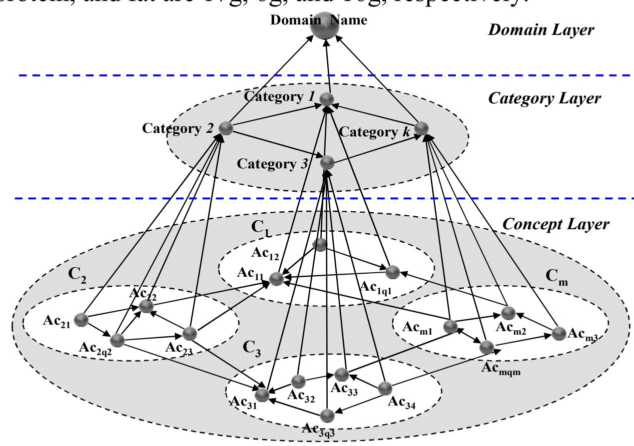

Fig. 2. Structure of the domain ontology.

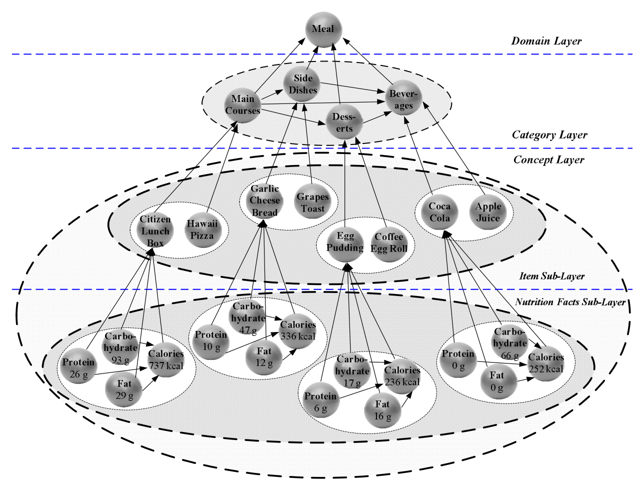

Fig. 3. Structure of the food ontology.

C. Fuzzy Markup Language

Acampora and Loia [12] proposed a Fuzzy Markup Language (FML), which is a fuzzy-oriented mark-up language that can manage fuzzy concepts, fuzzy rules, and fuzzy inference engine directly. Additionally, the FML is essentially composed of three layers, including eXtensible Markup Language (XML), document type definition, and extensible stylesheet language transformations [12]. Based on the FML, we developed an FML editor to construct the important knowledge base and rule base of the IHDPMA. The knowledge base describes the fuzzy concepts related to the fuzzy inference, including fuzzy variables, fuzzy terms, and membership functions of fuzzy sets. On the other hand, the rule base describes the fuzzy rule set, including the antecedent and consequence rule part. Fig. 4 shows the knowledge base and the rule base of the IHDPMA FML, where there are one output fuzzy variable (*Healthy Diet Status*, *HDS*), 729 fuzzy rules, and six input fuzzy variables, including *Age*, *Body Mass Index* (*BMI*), *Percentage of Calories from Carbohydrate* (*PCC*), *Percentage of Calories from Protein* (*PCP*), *Percentage of Calories from Fat* (*PCF*), and *Calories Difference* (*CD*). Each fuzzy variable has several fuzzy terms. For example, fuzzy variable *Age* has three fuzzy terms, namely "*Young*," "*Middle*," and "*Old*."

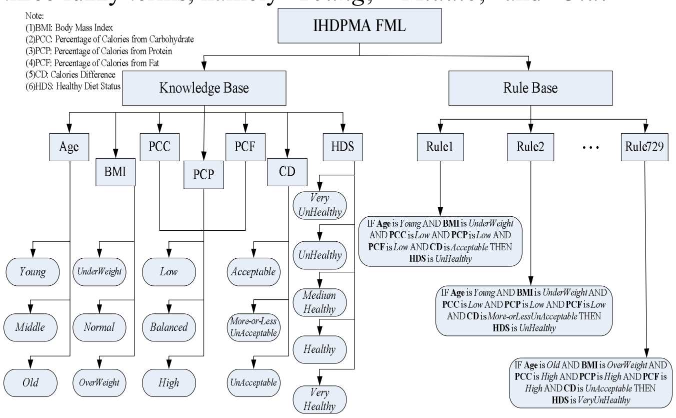

Fig. 4. The knowledge base and the rule base of the IHDPMA FML.

III. Intelligent Healthy Diet Planning Multi-Agent

The IHDPMA comprises six agents, including a *personal profile agent*, a *nutrition facts analysis agent*, a *knowledge analysis agent*, a *discovery agent*, a *fuzzy inference agent*, and a *semantic generation agent*, which are described below.

A. Structure of the IHDPMA

Fig. 5 shows the structure of the IHDPMA. First, the food data are gathered from the Internet and convenient stores in Taiwan. The processing mechanism then deals with the collected food data and transforms them into the information. Next, the extracting mechanism mines the information to the important knowledge and sends them into the acquiring mechanism. Fourth, the acquiring mechanism obtains the important knowledge and passes them to the domain experts. Fifth, the domain experts construct the FML and OWL using the FML editor and the protege [15], respectively, and store both of them into the *ontology repository*. Sixth, based on the pre-defined *ontology repository*, the IHDPMA finds out the user's personal profile, analyzes the nutrition facts of the meal records, calculates the percentage of calories from nutrients, discovers the necessary knowledge from the *ontology repository*, infers the possibility of healthy diet status, and eventually generates the semantic sentences. At last, the inferred results are stored into the healthy diet status repository and the domain experts then plan the healthy diet for the user on the basis of the inferred results. Fig. 6 shows the communication sequence among the sub-agents of the IHDPMA.

B. Personal Profile Agent

The *personal profile agent* plays a role in retrieving the user's personal profile, such as age, sex, height, weight, and BMI, from the profile ontology. Additionally, the past personal meal records also could be found by the *personal profile agent*.

C. Nutrition Facts Analysis Agent

In this study, the *nutrition facts analysis agent* is responsible of examining the number of carbohydrate, protein, and fat grams contained in one portion of the collected meals according to the pre-constructed food ontology. Meanwhile, how many calories are contained in one portion is also acquired.

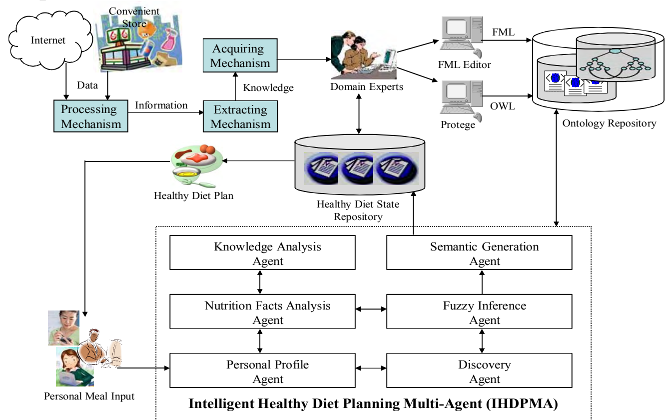

Fig. 5. Structure of the IHDPMA.

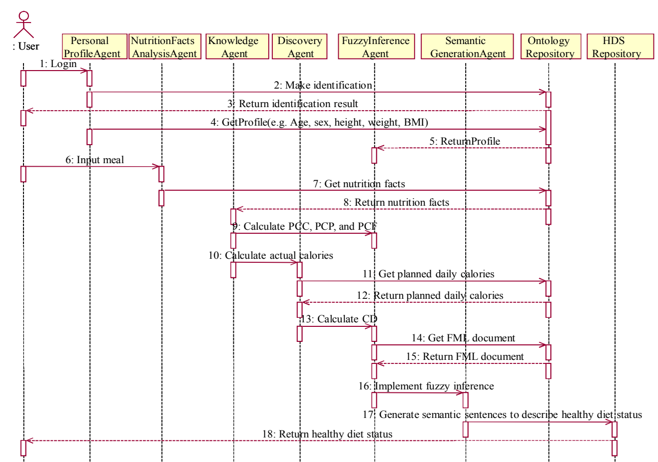

Fig. 6. Communication sequence of the IHDPMA.

D. Knowledge Analysis Agent & Discovery Agent

With the nutrition facts of eaten foods, the *knowledge analysis agent* further transforms them into the actual calories, the percentage of calories from carbohydrate, the percentage of calories from protein, and the percentage of calories from fat. The suggested percentages of calories from the carbohydrate, protein, and fat are 55%~65%, 10%~20%, and 25%~35%, respectively. The *discovery agent* then gets the planned daily calories to calculate the calories difference between the actual calories and planned calories.

E. Fuzzy Inference Agent

The *fuzzy inference agent* is the core of the proposed multi-agent system. Based on the pre-constructed FML document, it performs the fuzzy inference to infer the possibility of the healthy diet status. Fig. 7 shows parts of the knowledge base and rule base stored in the *ontology repository*. Table I shows the parameters of the membership functions, where a trapezoidal membership function for fuzzy set *FS* is specified by four parameters *FS*(*x*: *param1*, *param2*, *param3*, *param4*) and can be expressed as [*param1*, *param2*, *param3*, *param4*] [9]. The parameters of the membership functions are determined by the domain experts.

$$FS\,(x : param1, param2, param3, param4) = \begin{cases} 0 & x < param1 \\ (x - param1)/(param2 - param1) & param1 \le x < param2 \\ 1 & param2 \le x \le param3 \\ (param4 - x)/(param4 - param3) & param3 < x \le param4 \\ 0 & x > param4 \end{cases} \quad (1)$$

```
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- <FUZZYCONTROL defuzzifymethod="CENTROID" ip="localhost" type="MAMDANI">
 - <KNOWLEDGEBASE IP="localhost">
  - <FUZZYVARIABLE domainleft="20" domainright="60" ip="localhost" name="Age"
     scale="" type="INPUT">
   - <FUZZYTERM name="Young">
       <TRAPZOIDALSHAPE param1="20" param2="20" param3="25"
         param4="30" />
     </FUZZYTERM>
   - <FUZZYTERM name="Middle">
       <TRAPZOIDALSHAPE param1="25" param2="33" param3="38"
         param4="50" />
     </FUZZYTERM>
   - <FUZZYTERM name="Old">
       <TRAPZOIDALSHAPE param1="45" param2="50" param3="60"
         param4="60" />
     </FUZZYTERM>
   </FUZZYVARIABLE>
                              …
 </KNOWLEDGEBASE>
```

(a)

```
- <RULEBASE inferenceengine="MINMAXMAMDANI" ip="localhost">
 - <RULE connector="AND" ip="localhost" weight="1" id="R1">
  - <ANTECEDENT>
   - <CLAUSEA not="FALSE">
       <VARIABLE>Age</VARIABLE>
       <TERM>Young</TERM>
     </CLAUSEA>
   - <CLAUSEA not="FALSE">
       <VARIABLE>BMI</VARIABLE>
       <TERM>UnderWeight</TERM>
     </CLAUSEA>
   - <CLAUSEA not="FALSE">
       <VARIABLE>PCC</VARIABLE>
       <TERM>Low</TERM>
     </CLAUSEA>
   - <CLAUSEA not="FALSE">
       <VARIABLE>PCP</VARIABLE>
       <TERM>Low</TERM>
     </CLAUSEA>
   - <CLAUSEA not="FALSE">
       <VARIABLE>PCF</VARIABLE>
       <TERM>Low</TERM>
     </CLAUSEA>
   - <CLAUSEA not="FALSE">
       <VARIABLE>CD</VARIABLE>
       <TERM>Acceptable</TERM>
     </CLAUSEA>
    </ANTECEDENT>
  - <CONSEQUENT>
   - <CLAUSEC not="FALSE">
       <VARIABLE>HDS</VARIABLE>
       <TERM>UnHealthy</TERM>
     </CLAUSEC>
    </CONSEQUENT>
  </RULE>
                              …
 </RULEBASE>
</FUZZYCONTROL>
```

(b)

Fig. 7. Parts of the (a) knowledge base and (b) rule base.

TABLE I. PARAMETERS OF THE MEMBERSHIP FUNCTIONS.

Fuzzy Variable	Fuzzy Term	Trapezoidal Membership Function [*param1*, *param2*, *param3*, *param4*]
Age	Young	[20, 20, 25, 30]
	Middle	[25, 33, 38, 50]
	Old	[45, 50, 60, 60]
BMI	UnderWeight	[15, 15, 18.5, 20]
	Normal	[18.5, 20, 22, 24]
	OverWeight	[22, 24, 40, 40]
PCC	Low	[0, 0, 50, 55]
	Balanced	[50, 55, 65, 70]
	High	[65, 70, 100, 100]
PCP	Low	[0, 0, 5, 10]
	Balanced	[5, 10, 20, 25]
	High	[20, 25, 100, 100]
PCF	Low	[0, 0, 20, 25]
	Balanced	[20, 25, 35, 40]
	High	[35, 40, 100, 100]
CD	Acceptable	[0, 0, 50, 100]
	More-or-LessUnAcceptable	[70, 100, 150, 200]
	UnAcceptable	[150, 200, 5000, 5000]
HDS	VeryUnHealthy	[0, 0, 0.10, 0.25]
	UnHealthy	[0.10, 0.25, 0.25, 0.50]
	MediumHealthy	[0.25, 0.50, 0.50, 0.75]
	Healthy	[0.50, 0.75, 0.75, 0.90]
	VeryHealthy	[0.75, 0.90, 1.0, 1.0]

F. Semantic Generation Agent

The results of the *fuzzy inference agent* are transformed into the knowledge by the *semantic generation agent* to present the healthy diet status through the semantic descriptions according to the sentence patterns, listed in Table II. The algorithm of IHDPMA is shown in Table III.

TABLE II. SENTENCE PATTERNS.

***Semantic Analysis Sentence*:**

The eaten items at meal by this user exhibit that the person is at **[FN_{Age}: *Young*, *Middle*, *Old*]** age and the body mass index is **[FN_{BMI}: *UnderWeight*, *Normal*, *OverWeight*]**, meanwhile percentage of calories from carbohydrate is **[FN_{PCC}: *Low*, *Balanced*, *High*]**, percentage of calories from protein is **[FN_{PCP}: *Low*, *Balanced*, *High*]**, percentage of calories from fat is **[FN_{PCF}: *Low*, *Balanced*, *High*]**, and calories difference is **[FN_{CD}: *Acceptable*, *More-or-LessUnAcceptable*, *UnAcceptable*]**.

***Semantic Decision Sentence*:**

The IHDPMA justifies that the possibility of healthy diet status for meal is **[FN_{HDS}: *VeryUnHealthy*, *UnHealthy*, *MediumHealthy*, *Healthy*, *VeryHealthy*]**. (Possibility: **[0, 1]**)

TABLE III. IHDPMA ALGORITHM.

Intelligent Healthy Diet Planning Multi-Agent (IHDPMA) Algorithm

Input:

1. Input the *ontology repository*
2. Input the eaten meal set $\vec{M} \leftarrow$

   $\{[\,MainCourse_{\,1},\ldots,MainCourse_{\,N}\,],$

   $[\,SideDish_{\,1},\ldots,SideDish_{\,Q}\,],$

   $[\,Dessert_{\,1},\ldots,Dessert_{\,R}\,],$

   $[\,Beverage_{\,1},\ldots,Beverage_{\,L}\,]\}$

   /*where *N*, *Q*, *R*, and *L* denote the number of food items grouped into main course, side dish, dessert, and beverage, respectively.*/
3. Input the portions of the eaten meal set $\vec{P} \leftarrow$

   $\{[\,Portion\_MainCourse_{\,1},\ldots,Portion\_MainCourse_{\,N}\,],$

   $[\,Portion\_SideDish_{\,1},\ldots,Portion\_SideDish_{\,Q}\,],$

   $[\,Portion\_Dessert_{\,1},\ldots,Portion\_Dessert_{\,R}\,],$

   $[\,Portion\_Beverage_{\,1},\ldots,Portion\_Beverage_{\,L}\,]\}$

Output:

1. Healthy diet status set Set_{HDS}
2. Semantic analysis for the eaten meal

Method:

Step1: If user's identification is passed **Then**

Step1.1: Retrieve the user's Age ($Value_{Age}$), Height($Value_{Height}$), and Weight($Value_{Weight}$) from the *ontology repository* to calculate the user's *BMI* by $Value_{BMI} \leftarrow Value_{Weight} \big/ {Value_{Height}}^2$

Step2: Retrieve nutrition facts (calories per portion, the number of carbohydrate, protein, and fat grams contained in one portion) of eaten main courses, side dishes, desserts, and beverages from the *ontology repository*.

$\vec{C} \leftarrow$

$\{[\,C\_MainCourse_{\,1},\ldots,C\_MainCourse_{\,N}\,],$

$[\,C\_SideDish_{\,1},\ldots,C\_SideDish_{\,Q}\,],$

$[\,C\_Dessert_{\,1},\ldots,C\_Dessert_{\,R}\,],$

$[\,C\_Beverage_{\,1},\ldots,C\_Beverage_{\,L}\,]\}$

$\vec{G}_{Carbohydrate} \leftarrow$

$\{[\,G_{Carbohydrate}\_MainCourse_{\,1},\ldots,G_{Carbohydrate}\_MainCourse_{\,N}\,],$

$[\,G_{Carbohydrate}\_SideDish_{\,1},\ldots,G_{Carbohydrate}\_SideDish_{\,Q}\,],$

$[\,G_{Carbohydrate}\_Dessert_{\,1},\ldots,G_{Carbohydrate}\_Dessert_{\,R}\,],$

$[\,G_{Carbohydrate}\_Beverage_{\,1},\ldots,G_{Carbohydrate}\_Beverage_{\,L}\,]\}$

$\vec{G}_{Protein} \leftarrow$

{[$G_{Protein}\_MainCourse_1,\ldots,G_{Protein}\_MainCourse_N$],
[$G_{Protein}\_SideDish_1,\ldots,G_{Protein}\_SideDish_Q$],
[$G_{Protein}\_Dessert_1,\ldots,G_{Protein}\_Dessert_R$],
[$G_{Protein}\_Beverage_1,\ldots,G_{Protein}\_Beverage_L$]}

$\vec{G}_{Fat} \leftarrow$
{[$G_{Fat}\_MainCourse_1,\ldots,G_{Fat}\_MainCourse_N$],
[$G_{Fat}\_SideDish_1,\ldots,G_{Fat}\_SideDish_Q$],
[$G_{Fat}\_Dessert_1,\ldots,G_{Fat}\_Dessert_R$],
[$G_{Fat}\_Beverage_1,\ldots,G_{Fat}\_Beverage_L$]}

Step3: Calculate the total calories intake, the total calories from carbohydrate, protein, and fat, respectively, by

Step3.1: $\vec{C}_{Actual} \leftarrow \sum \vec{C} \times \vec{P}$

Step3.2: $\vec{C}_{Carbohydrate} \leftarrow (\sum \vec{G}_{Carbohydrate} \times \vec{P}) \times 4$

Step3.3: $\vec{C}_{Protein} \leftarrow (\sum \vec{G}_{Protein} \times \vec{P}) \times 4$

Step3.4: $\vec{C}_{Fat} \leftarrow (\sum \vec{G}_{Fat} \times \vec{P}) \times 9$

Step4: Calculate the values of *PCC*, *PCP*, and *PCF* by

Step4.1: $Value_{PCC} \leftarrow (\vec{C}_{Carbohydrate} / \vec{C}_{Actual}) \times 100\%$

Step4.2: $Value_{PCP} \leftarrow (\vec{C}_{Protein} / \vec{C}_{Actual}) \times 100\%$

Step4.3: $Value_{PCF} \leftarrow (\vec{C}_{Fat} / \vec{C}_{Actual}) \times 100\%$

Step5: Retrieve the planned calories needs ($\vec{C}_{Planned}$) from the *ontology repository*

Setp6: Calculate the value of *CD* by

$Value_{CD} \leftarrow |\vec{C}_{Planned} - \vec{C}_{Actual}|$

Step7: Retrieve the FML document (IHDPMA.xml) from the *ontology repository*

Step8: Based on the IHDPMA.xml, implement the fuzzy inference.

Let $X \leftarrow [(Value_{Age}, Value_{BMI}, Value_{PCC}, Value_{PCP}, Value_{PCF}, Value_{CD})]$

Step8.1: For $k \leftarrow$ *1 to K* /**K* denotes the number of fuzzy rules*/

Step8.1.1: Calculate the matching degree of the *Rule k* by

$\mu_k \leftarrow MIN(\mu_{A_{in}}(X))$

Step8.1.2: Calculate the center of area of the *Rule k* by

$y_{A_{out}}\_k \leftarrow COA(\mu\_k)$

Step8.2: For $t \leftarrow$ *1 to T*

Step8.2.1: Calculate the membership values of X to the fuzzy classes F_t by $y_t \leftarrow MAX(y_{A_{out}}k)$

where F_t means the fuzzy class for all of fuzzy rules. Each fuzzy class is an aggregation of the fired rules that have the same consequences

Step8.2.2: Defuzzify into a crisp value by

$$HDS \leftarrow \sum_{t=1}^{T} w_t y_t \Big/ \sum_{t=1}^{T} w_t$$

where w_t means the weight for y_t and T means the number of fuzzy numbers of the output fuzzy variables, *HDS*

Step8.2.3: Add HDS to Set_{HDS}

Step9: Generate the semantic description based on the inferred results and Table II.

IV. EXPERIMENTAL RESULTS

The IHDPMA platform was a built Active Server Pages (ASP).Net website using Microsoft C# programming language. This study focuses on people who are aged from 20 to 60 years old and with the average levels of physical activity. Twenty students of National University of Tainan (NUTN), Taiwan were involved in this experiment. They recorded their dinner meals from Monday to Friday for about one month. Therefore, 20 records were collected for each volunteer. Herein, we take one of volunteers, a 30-year-old man with 60 kilograms, and 170centimeters, as an example to describe the experiments. In the first experiment, we test the performance of the IHDPMA according to the collected records of 20 dinner meals. The No. 2 meal, which displays that if the involved volunteer eats one portion of "Seafood rice with cheese," one portion of "Mexican grapes buttery bread," one portion of "Chocolate balls with peanut," and one portion of "Apple juice," then both the domain experts and the IHDPMA justify that the eaten meal is "*VeryUnHealthy*." It indicates that the involved volunteer had better try not to eat this kind of food as often as possible in order to keep healthy. On the other hand, the experimental result of meal No. 19 is that both the domain experts and the IHDPMA justify that this meal is "*VeryHealthy*." Therefore, it is helpful for the involved volunteer to eat meal No. 19. The detailed experimental results of meals Nos. 2 and 19 are listed in Table IV.

TABLE IV. RESULTS OF MEALS NOS. 2 AND 19.

No	Semantic Descriptions of Healthy Diet Status for eaten items at meal					
2	Age	BMI	PCC	PCP	PCF	CD
	30	20.76	58.42	9.58	31.99	709.62
	The eaten items at meal by this user exhibit that the person is at ***Middle*** age and the body mass index is ***Normal***, meanwhile percentage of calories from carbohydrate is ***Balanced***, percentage of calories from protein is ***Low***, percentage of calories from fat is ***Balanced***, and calories difference is ***UnAcceptable***. The IHDPMA justifies that the possibility of healthy diet state for meal is ***VeryUnHealthy***. (Possibility: **0.1**)					
	The domain experts justifies that the meal is ***VeryUnHealthy***.					
19	Age	BMI	PCC	PCP	PCF	CD
	30	20.76	64.27	8	27.73	84.58
	The eaten items at meal by this user exhibit that the person is at ***Middle*** age and the body mass index is ***Normal***, meanwhile percentage of calories from carbohydrate is ***Balanced***, percentage of calories from protein is ***Low***, percentage of calories from fat is ***Balanced***, and calories difference is ***Acceptable***. The IHDPMA justifies that the possibility of healthy diet status for meal is ***VeryHealthy***. (Possibility: **0.81**)					
	The domain experts justifies that the meal is ***VeryHealthy***.					

The second experiment is to observe the variance in the possibility of healthy diet status evaluated by the domain experts and the IHDPMA. Fig. 8 shows the curves of possibility of healthy diet status expected by the domain experts and the IHDPMA, respectively. Additionally, Fig. 8 also shows the curves of difference between the domain experts and the IHDPMA. It reveals that the difference between the domain experts and the IHDPMA of meals No. 1-20 is below 0.25. The final experiment is to evaluate the *accuracy*, *precision*, and *recall* for the IHDPMA. Table V shows four different possible outcomes of a single prediction [8]. The *accuracy*, *precision*, and *recall* are calculated by (2), (3) and (4), respectively. Based on various threshold bounded in the interval of [0.05, 0.90], Fig. 9 shows the curves of *accuracy*, *precision*, and *recall*. Herein, the threshold denotes the membership degree threshold for *HDS*. It reveals that the *accuracy* is 90% when the threshold is from 0.55 to 0.70. It also indicates that the *recall* and *precision* are inversely related. As the *recall* increases, the *precision* decreases, and vice versa.

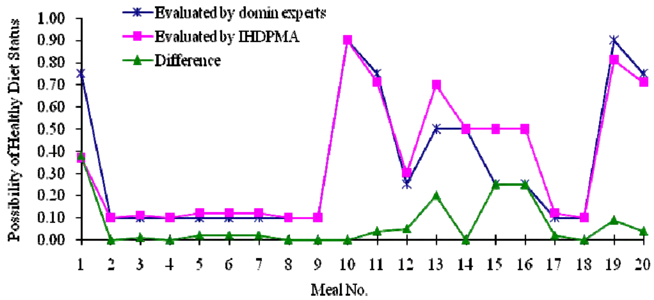

Fig. 8. Curves of the possibility of healthy diet status.

TABLE V. CLASSIFICATION OF RESULTS.

Actual class	Predicted class	
	Yes	No
Yes	True positive (*TP*)	False Negative (*FN*)
No	False positive (*FP*)	True Negative (*TN*)

$$Accuracy = (TN+TP)/(TN+FN+FP+TP) \times 100\% \quad (2)$$
$$Precision = TP/(TP+FP) \times 100\% \quad (3)$$
$$Recall = TP/(TP+FN) \times 100\% \quad (4)$$

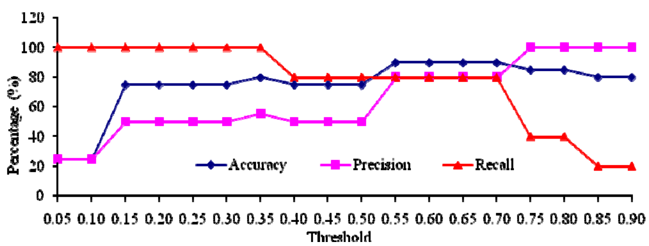

Fig. 9. Curves of the *accuracy*, *precision*, and *recall*.

V. CONCLUSION

An intelligent multi-agent system, including a *personal profile agent*, a *nutrition facts analysis agent*, a *knowledge analysis agent*, a *discovery agent*, a *fuzzy inference agent*, and a *semantic generation agent*, is proposed in this study, which describes how fuzzy rules and fuzzy sets can be used to represent conceptual data based on physical characteristics of an individual and an opinion on the diet. Experimental results show that the proposed system enables an intelligent behavior able to generate the more suitable healthy diet for a given human being. Additionally, combined with the ontology, the proposed multi-agent system becomes much intelligent. With the support of the proposed agent, it not only can help a human eat healthily and keep his body in top shape but also cut down the workload of a medical domain expert. In the future, introducing the concept of type-2 fuzzy set to the follow-up researches, comparing the IHDPMA to other existing prior art are considered. In addition, the eating habit of the person, the time of day the person eats, whether the person eats in-between meals, life style of the person, and when the person consumes a high calorie meal will also be taken into considerations in the future. It is hoped that the performance will be get better than now.

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