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Fuzzy Expert System Generalised Model for Medical Applications

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***Abstract* – Over the past two decades an exponential growth of medical fuzzy expert systems has been observed. These systems address specific forms of medical and health problems resulting in differentiated models which are application dependent and may lack adaptability. This research proposes a generalized model encompassing major features in specialized existing fuzzy systems. Generalization modelling by design in which the major components of differentiated the system were identified and used as the components of the general model. The prototype shows that the proposed model allows medical experts to define fuzzy variables (rules base) for any medical application and users to enter symptoms (facts base) and ask their medical conditions from the designed generalised core inference engine. Further research may include adding more composition conditions, more combining techniques and more tests in several environments in order to check its precision, sensitivity and specificity.**

***Keywords* – Expert system, fuzzy logic, generalized model, medical applications.**

I. Introduction

Real world phenomena are described in linguistic terms such as “hot” or “heavy” with quantification qualifiers like very, slightly, not, much, etc. To handle such phenomena, computer applications have to migrate from classical “no-membership / full membership” variables to fuzzy variables [1], [2]. Due to many advantages of such a higher linguistic system, fuzzy logic application areas have spread in aerospace, automotive and marine transportation areas; in business, financial and commercial analysis; in defence and security; in electronics, manufacturing and industrial control sectors; pattern recognition and classification, in psychology and medicine; and in many more sectors [3]– [11].

The interest of various researchers for the development of fuzzy applications in the medical field has been accelerated [14], [15] in last two and half decade. In [12] and [13] authors reveal that the trend of research in medical fuzzy expert systems shows an exponential growth in specific medical applications. However, since each of these fuzzy applications addresses specific form of medical or health problem (disease), they have been observed to be application dependent. Moreover, as each medical fuzzy system is a special case, knowledge transfer from medical experts to computer scientists for system development would lead to a perpetual recommencement.

With these problems in view, there is need for application independent, general and intelligent models. The aim of this research is to design a fuzzy model that will encompass major features in specialized existing fuzzy systems. Hence, this research targets the following objectives: (i) gather a good number of differentiated medical fuzzy system models by a comprehensive medical expert system survey, (ii) design meta knowledge base ruler for a medical generalized fuzzy system including a rule base meta-model and a fact base meta-model, (iii) provide a prototype which allows medical experts to define fuzzy variables and facts for any medical application and run them over the generalized core inference engine.

II. Research Background

Many studies have been performed in times past with respect to developing medical fuzzy systems for diagnosis and predictive-related informatics applications. The first relevant achievement is the Fuzzy set theory and fuzzy logic proposed in the 1960s by Zadeh to manage imprecise and vague knowledge [1], [3] with the ambition to provide interaction of natural language and numerical models [16]. Since then a number of fuzzy system models have been proposed. In medical applications, we reccord succesfull fuzzy systems ranging from AAPHelp, INTERNIST and MYCIN in the 1970s [17] – to contemporary sophisticated systems [12], [13], [21], [22].

Fuzzy logic has penetrated almost all medical applications [23]. One major reason is that medical, biomedical, and health sectors deal with imprecise, approximate and vague knowledge in which linguistic variables have partial truth that ranges in degree between completely true and completely false. Hence, fuzzy logic is used in these fields for three main raisons. First, it defines inexact medical entities as fuzzy sets. Second, it provides a linguistic approach with an excellent approximation. Finally, fuzzy logic offers reasoning methods capable of drawing medical inferences [3].

Existing medical artificial intelligence programs simulate the manner of expert and they are designed and developed in such a way that patients can independently use them. Based on symbolic models of disease entities and their relationship to patient factors and clinical manifestations, they are found in all the phases in clinical care, such as diagnosis before therapy, or prevention of disease before onset of disease, or rehabilitation of the patient after therapy [23]. A close look at these models shows that each addresses specific form of medical problem. Apart from possible similarities, none of these systems can be

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adapted to quickly fit the need of another system. Any other fuzzy medical system must restart from scratch and have its own and independent knowledge base. The paper solves this problem by using generalised fuzzy expert system and set theories to come up with a fuzzy medical generalised model.

III. Research Methodology

The research focuses on generalization modelling because a sufficient number of differentiated models have been proposed and it is now possible to observe the trends in these models and propose general models. The method uses those differentiated models (produced by clarification modelling, and differentiation modelling) to build general and generic models at the maturity stage. The approach used is there search is "modelling by design", in which the major components of the system are identified and used as the components of the general model [24].

In terms of modelling techniques, the research uses a three-step technique of fuzzy logic [25]: system input/output fuzzy quantification, system input and output linking (input composition and rule combination) and output defuzzification. During fuzzy quantification, we have used triangular and trapezoidal membership function for fuzzy sets. Linear as opposed to curves membership parametric functions have been used due to their simplicity and efficiency with respect to compatibility [3].

Since medical systems are multiple input systems, the model in the research defines an IF Fuzzy Rule Base Relational $N \times 3$ matrix to contain the system N rules defined by their codes, conditions and their consequences. Each rule derives a membership degree computed from inputs in its condition. When inputs in the rule condition are linked by logical operators, the membership degree is computed by a composition function depending on operator meaning. Rule consequence is an output set element computed from the condition input degree of membership by the defuzzification function.

Likewise, when more than one rule from the Rule Base are likely infer the output with different output values, a maximum technique is used for being simple with better performance in terms of continuity and computer complexity [26], [27].

IV. Research Results

A. Differentiated Medical Fuzzy System Models

The surveys performed by Metaxiotis and Samouilidis [23], by Patel and colleagues [12], by Mishraand and Prakash [15] and by Nath and Prasenjit [17] associated with our own survey [1], [3], [13], [14], [16], [19], [20], [26], [28] that fuzzy logic application in medicine has gone through the development stage and produced differentiated models. The finding is that all of them have the following common features: (a) symptom identification, (b) symptom fuzzy set definition (fuzzification), (c) rule base definition, (d) output defuzzification, (e) fact establishment and (f) system test. Based on these functionalities, Fig. 1 sketches the architectural design of the proposed system, in which the characteristics of all specific systems are addressed.

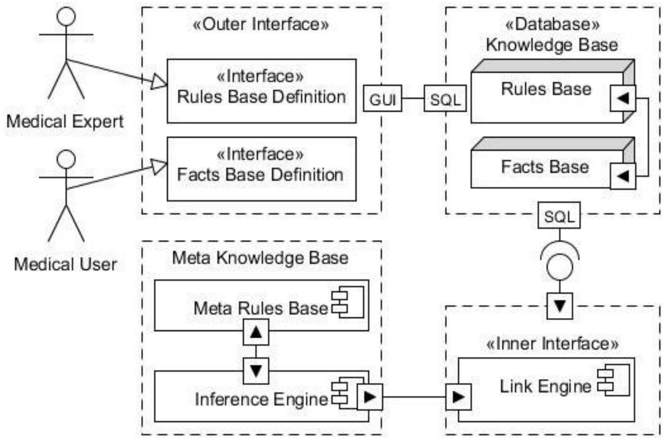

Fig. 1. Architectural design of a general medical fuzzy system.

B. Input and Output Fuzzification

Any health concern is characterised by directly observable symptoms: a series of clinical and para-clinical observations. These symptoms are usually the deviation of the observations from their normal state (value) and they are expressed by affirmations like hot, dark, dirty, deep, etc. These expressions are sets to which a person (or any entity) with a specific characteristic value belongs at some extent (degree). More formally, a medical phenomenon is a set of characteristic values called are reference (Crisp) set ($X = \{x_1, x_2, \ldots, x_n\}$) and a fuzzy subset A of affirmations on X defined by a membership function $\mu A(x)$, which assigns any $x \in X$ to a value in the interval of real numbers between 0 and 1 (0 means no-membership and 1 – full membership). $\mu A(x)$ represents the extent to which x can be considered as an element of X. Hence, the following parameters have been included in the model [27] to formalise every manifestation (called field in the present research) within a medical phenomenon:

1. Input field and its measurement instrument;
2. Fuzzy sets for each input field (called symptoms in the research);
3. Fuzzy set (symptoms) respective threshold values (called class boundaries):
   a. Full phenomenon values (F_1, F_2) above which the membership degree is 1;
   b. Empty phenomenon values (E_1, E_2] under which the membership degree is 0;
4. The fuzzy membership trapezoidal function computed by Function 1 (see Fig. 2). When $F_1 = F_2$, $E_1 = 2$ or $F_2 = E_2 = \infty$, the membership function becomes triangular.

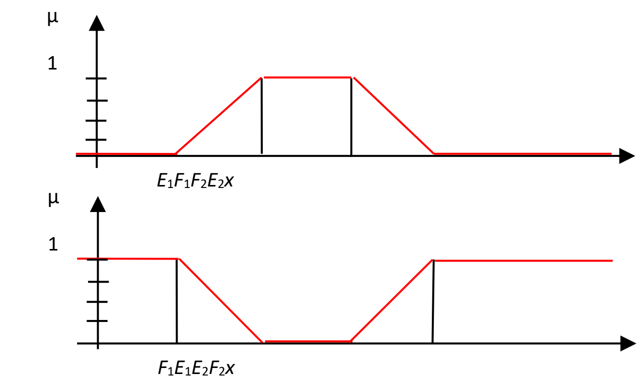

Fig. 2. Membership trapezoidal function.

$$\mu(x,E_1,E_2,F_1,F_2)=\begin{cases} 1: \text{WHEN } x \in (-\infty,F_1] \text{ AND } F_1<E_1 \\ 1: \text{WHEN } x \in [F_1, \quad F_2] \text{ AND } F_1>E_1 \\ 1: \text{WHEN } x \in [F_2,+\infty) \text{AND} F_1<E_1 \text{AND } E_2>E_1 \\ 1: \text{WHEN } x \in [E_2,+\infty) \text{ AND} F_1>E_1 \text{AND } F_2=F_1 \\ \dfrac{x-E_1}{F_1-E_1}: \text{WHEN } x \in [E_1,F_1] \text{ AND } F_1>E_1 \\ \dfrac{E_2-x}{E_2-F_2}: \text{WHEN } x \in [F_2,E_2] \text{ AND } F_1>E_1 \\ 1-\dfrac{x-F_1}{E_1-F_1}: \text{WHEN } x \in [F_1,E_1] \text{ AND } F_1<E_1 \\ 1-\dfrac{F_2-x}{F_2-E_2}: \text{WHEN } x \in [E_2,F_2] \text{ AND } F_1<E_1 \\ 0: \text{WHEN } x \in [E_1,E_2] \text{ AND } F_1<E_1 \\ 0: \text{WHEN } x \in (-\infty,E_1] \text{ AND } F_1>E_1 \\ 0: \text{WHEN } x \in [E_2,+\infty) \text{ AND } F_1>E_1 \text{ AND } F_2>F_1 \\ 0: \text{WHEN } x \in [F_2,+\infty) \text{ AND} F_1<E_1 \text{ AND} E_2=E_1 \end{cases}$$

Function 1: Input membership fuzzy function.

C. Input and Output Linking

The ultimate objective of a fuzzy system is to compute an output value. To achieve the objective, two steps (Fig. 3) have been set. First, after input and output fuzzification, the fuzzy inference function evaluates the control rules stored in the fuzzy rule base and produces the fuzzy output membership value (Function 2). In practice, medical output is linked to more than one input. Two complementary actions are then needed: input membership degree composition (Function 3) and input rule combination processing (Function 4).

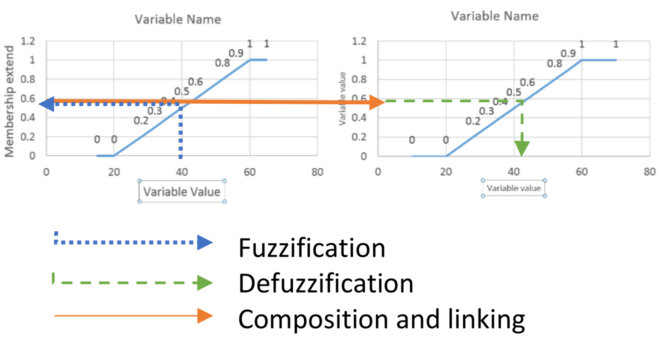

Fig. 3. Output composition and defuzzification.

Second, defuzzification function converts the fuzzy output membership degree from the first step to real crisp values in the linguistic value (Function 5).

The output fuzzy membership function f_{link}: [0–1]→[0–1] [1] finds the output membership degree from the input membership degree. The input-output relation can be either directly proportional or inversely proportional (Function 2).

$$\mu(\mu(x),\text{type})=\begin{Bmatrix} \mu(x) \text{ WHEN type} = \text{proportional} \\ (1-\mu(x)) \text{ WHEN type} = \text{inv. prop} \end{Bmatrix}.$$

Function 2: Output fuzzy membership function.

D. Input Membership Degree Composition

When the medical input rule has complex conditions, in which inputs are linked by logical operators, the following function is used for input membership composition into one membership degree to be used in Function 2 above:

$$f_{\text{composition}}(\mu(x_1),\mu(x_2),op)=$$
$$=\begin{Bmatrix} \min(\mu(x_1),\mu(x_2)) \text{ WHEN } op=\text{AND} \\ \max(\mu(x_1),\mu(x_2)) \text{ WHEN } op=\text{OR} \end{Bmatrix}.$$

Function 3: Membership degree composition.

E. Input Rule Combination

Generally, given one input, several input rules might be simultaneously validated and give different output degrees, the following input rule combination function is used to compute the final degree to be used with vty, the validity associated with each rule:

$$f_{\text{combination}}(\mu(Rule_1),..,\mu(Rule_n),vty_1,..,vty_n)=$$
$$=\{(\mu(Rule_i)) \text{ WHEN } vty_i=\max(vty_1,..,vty_n)\}.$$

Function 4: Rule composition function.

F. Output Defuzzification

During defuzzification, membership functions are used to retranslate the fuzzy output membership degree into a crisp value. Function 5 is used to compute the probability of the membership degree 9 computed by the link between input and output to result in an output fuzzy set. This membership degree is as follows:

$$f(\mu(x),E_1,F_1,F_2,E_2)=$$
$$=\begin{Bmatrix} F_1 \ : \text{ WHEN } \mu(x)\in[1,1] \\ E_1+[(F_1-E_1)\times\mu(x)]: \text{WHEN } \mu(x)\in[0,1] \\ E_1: \text{WHEN } \mu A(x)\in[0,0] \end{Bmatrix}.$$

Function 5: Output membership fuzzy function.

V. Research Prototype and Test Results

A. Test Prototype

In order to test and prove the workability of our general model, a prototype was built using SwiProlog, PHP and MySql. SwiProlog was used to build the rule base and provided the inference engine. It is the core of the proposed fuzzy expert system model. Listing 1 shows the last part of the proposed rule base.

```
% Linking Inpout and Output : 0=prop., 1=inverse prop.
linking(InDeg,Type,OutDeg):-Type=0,OutDeg is InDeg.
linking(InDeg,Type,OutDeg):-Type=1,OutDeg is 1-InDeg.
linking(In1,In2,Op,Type,OutDeg):-
composition(In1,In2,Op,Out),linking(Out,Type,OutDeg).
linking(In1,X,E1,E2,F1,F2,Op,Type,OutDeg):-
fuzzy(X,E1,E2,F1,F2,F),linking(In1,F,Op,Type,OutDeg).
% Input Composition 0 is AND, 1 is OR,...
composition(In1,In2,Op,Out):-Op=1,In1=<In2,Out is In2.
composition(In1,In2,Op,Out):-Op=1,In1>In2,Out is In1.
composition(In1,In2,Op,Out):-Op=0,In1=<In2,Out is In1.
composition(In1,In2,Op,Out):-Op=0,In1>In2,Out is In2.
% Test
whatDegree(X,E1,E2,F1,F2,F):-fuzzy(X,E1,E2,F1,F2,F),
write('Degree for '),write(X),write('is '),write(F),write('%').
deg(X,E1,E2,F1,F2,F):-fuzzy(X,E1,E2,F1,F2,F),write(F).
linkDeg(In1,X,E1,E2,F1,F2,Op,Type,OutDeg):-
linking(In1,X,E1,E2,F1,F2,Op,Type,OutDeg),write(OutDeg).
```

Listing1. SwiProlog part of the proposed rule base.

PHP, HTML and CSS were used to build the user interface and the engine which links the database to the core fuzzy expert system model (Listing 2).

```
<?php
$sql1="SELECT * FROM `base_regles`,`coditions`,
`maladie_symptomes`,`actual_sympto`
WHERE CodeReg=NumReg AND sypCode=CodeSympt AND
FieldCode=Field AND CodeReg='".$_POST['levPlm']."'
ORDER BY CodeReg ASC
LIMIT 0 , 100";
while($rows=mysql_fetch_array($result)){
    $cmd = '"C:\Program Files\swipl\bin\swipl.exe" -g
    deg('.$rows['symptVal'].','.$rows['E1'].','.$rows['E2'].','.$row
    s['F1'].','.$rows['F2'].',Fuzzy) -t halt(1) test.pl';
    $cm = '"C:\Program Files\swipl\bin\swipl.exe" -g
    linkDeg('.$deg.','.$rows['symptVal'].','.$rows['E1'].','.$rows['
    E2'].','.$rows['F1'].','.$rows['F2'].','.$op.',0,OutDeg) -t halt(1)
    test.pl';
    $outPrev=shell_exec( $cmd );
    $outpu = shell_exec( $cm );
    echo'<input type="text" name="query2"
    value="'.$rows['ConsReg'].'--'.$rows['sypCode'].'( '.$curr.') :
    >>> '.$fuzVar. ': >>> '.$fx.'('.$deg.','.$curr.')='.$deg.'"
    size="90"/><br>';
    $nb++;
}
echo 'Degree to apply at this level of composition for '.$old.' is :
'.$deg.' (Say : '.$perc.'% )<br>';
echo 'Number of symptoms : <input type="text"
name="symptNumb" value ="'.$nb.'"size="2" /> Operation used
:<input type="text" name="symptNumb" value
="'.$myOp.'"size="2" />';
?>
```

Listing 2. PHP/HTMLlinking program.

MySql was used to hold both metadata to feed the rule base and actual data to feed the user fact base. Figure 4 shows part of the proposed MySql database structure.

B. Test Data

- Test Case Presentation

Using a simplified version of the medical example provided in [3] and [28], let us consider the clinical statement that someone can have Ebola Haemorrhagic Fever into three different stages, say “No Ebola”, “Medium Ebola” and “Severe Ebola”. Three clinical fields have been considered as an experimental sample: Body Temperature (Fever), Vomiting and Contact with a person with Ebola Haemorrhagic Fever.

A person is said to have “No Ebola”, he has No Fever and he has No Vomiting and has No Contact condition. He is said to have “Medium Ebola when his condition is Medium Fever, Medium Vomiting and No Contact. Last, someone has a “Severe Ebola” when his condition is Severe Fever, Severe Vomiting and a Suspected Contact.

The question to be answered by the expert system is: “what would be the Ebola state of someone who is not vomiting, whose body temperature is 36.75 °C, and had a suspect contact?”

- Test Case Rule Base

The following MySql table shows fuzzy sets (a), rules (b) and rule condition (c), respectively.

mlCode	FieldCode	sypCode	E1	E2	F1	F2
Malaria		Fievre	36	42	37	37
Malaria		Taux	10	40	20	30
Malaria		Diarhee	10	10	25	25
Ebola	Fievre	No Fever	37	37	36	36
Ebola	Fievre	Med Fever	36	39	37	38
Ebola	Fievre	Severe Fever	38	38	39	39
Ebola	Vomis	No Vomit	1	1	0	0
Ebola	Vomis	Med Vom	0	10	5	5
Ebola	Vomis	Severe Vom	5	5	10	10
Ebola	Contact	No Contact	1	1	0	0
Ebola	Contact	SuspContact	0	0	1	1

(a)

NumReg	ConsReg	OpReg
NonMa	No Ebola	AND
MedMa	Medium Ebola	AND
FortMal	Severe Ebola	AND

(b)

CodeReg	CodeSympt
NonMa	No Contact
NonMa	No Fever
NonMa	No Vomit
MedMa	Med Fever
MedMa	Med Vom
MedMa	No Contact
FortMal	Severe Fever
FortMal	SuspContact
FortMal	Severe Vom

(c)

Fig. 4. Rule base database.

• Test Fact Base

Figure 5 shows the fact in hand, say actual measurements taken from a particular potential Ebola Haemorrhagic Fever patient A001.

PatCode	MalCode	Field	symptVal
A001	Malaria	Taux	18
A001	Malaria	Diarhee	15
A001	Ebola	Fievre	38.4
A001	Ebola	Vomis	3
A001	Ebola	Contact	0.4

Fig. 5. Fact base database.

C. Test Results

Figure 6 shows some sample results: meta-model definition (a), membership degree per output set after input set composition (b) and membership degree for all output sets after input set composition and rule combining (c).

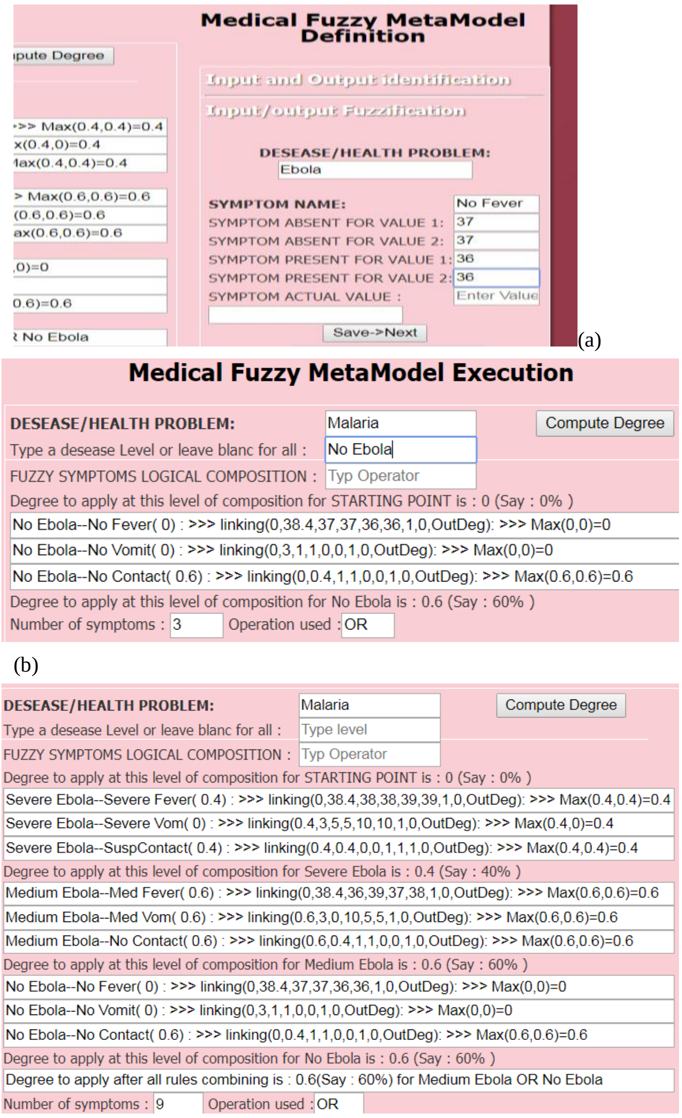

Fig. 6. Generalised model test sample results.

VI. Conclusion and Discussion

Findings of the research reveal an exponential growth of medical fuzzy expert systems addressing specific form of medical and health problems. In addition, existing differentiated medical fuzzy system models are application dependent and, hence, suffer from a lack of adaptability. A generalised medical fuzzy system model solves this problem.

The proposed generalised model encompasses features in specialised existing fuzzy systems and, hence, constitutes a solution to this problem. The system test prototype shows that the model allows medical experts to define fuzzy variables (rule base) for any medical application and users to enter symptoms (fact base) and ask their medical conditions from the designed generalised core inference engine.

Compared to other application dependent systems, this model reveals itself to be more general, practical and easy-to-use by a medical expert and users. Hence, it creates a new paradigm for future studies of the evolution of medical fuzzy systems. Further research may enrich the model by adding more composition condition operators and more combining techniques, such as centre of sum, centre of area, mean of maximum [26], balanced average and the centroid method [27]. Furthermore, the model needs to be tested in several environments to check its precision, sensitivity and specificity.

Conflict of Interest Statement

The author works alone and the project is not yet funded, hence declare no conflict of Interest.

Appendix: Demonstration Software Prototype

The system prototype software associated with this article is freely available at http://alis.muyisa.com/stat.php: Login “lin”, Password “1234”. Click on “Mode passe correcte” link, then choose the menu “Chat”.

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