Agent Metaphor for Machine Translation Mediated Communication

Chunqi Shi
Kyoto University
Yoshida-Honmachi,
Sakyo-Ku, Kyoto
shi@ai.soc.i.kyoto-u.ac.jp

Donghui Lin
Kyoto University
Yoshida-Honmachi,
Sakyo-Ku, Kyoto
lindh@i.kyoto-u.ac.jp

Toru Ishida
Kyoto University
Yoshida-Honmachi,
Sakyo-Ku, Kyoto
ishida@i.kyoto-u.ac.jp

ABSTRACT
Machine translation is increasingly used to support multilingual communication. Because of unavoidable translation errors, multilingual communication cannot accurately transfer information. We propose to shift from the transparent-channel metaphor to the human-interpreter (agent) metaphor. Instead of viewing machine translation mediated communication as a transparent channel, the interpreter (agent) encourages the dialog participants to collaborate, as their interactivity will be helpful in reducing the number of translation errors, the noise of the channel. We examine the translation issues raised by multilingual communication, and analyze the impact of interactivity on the elimination of translation errors. We propose an implementation of the agent metaphor, which promotes interactivity between dialog participants and the machine translator. We design the architecture of our agent, analyze the interaction process, describe decision support and autonomous behavior, and provide an example of repair strategy preparation. We conduct an English-Chinese communication task experiment on tangram arrangement. The experiment shows that, compared to the transparent-channel metaphor, our agent metaphor reduced human communication effort by 21.6%.

Author Keywords
Machine translation mediated communication; interactivity; repair strategy; agent;

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation: Miscellaneous - *Computer-mediated communication*

INTRODUCTION
Multilingual communication connects people from different nations, encourages business, and brings transnational cooperation. Given the success of famous companies, such as Facebook and Amazon, the need for multilingual communication is obvious. Thus, efficient support tools continue to receive more attention [9]. Machine translation always plays an important role in the implementation of such tools. For example, machine translation has been integrated in a communication support agent developed for multilingual participatory gaming [25]. However, machine translation has limits in terms of translation quality [26]. The translation errors continue to be the barrier for machine-translation-mediated (MT-mediated) communication. When MT-mediated communication is used for a cooperation task, it is necessary to translate the task-oriented dialog accurately. Generally speaking, a communication dialog can be tagged as task-oriented, emotion-oriented, or both [17]. According to social information process theory, emotion-oriented dialog involves not only the cognitive process but also the emotion transfer process. Task-oriented dialog mainly focuses on the acquisition of information in the task domain [3]. In machine translation of task-oriented dialogs, the accurate translation of concepts is the basis of successful information transfer [27]. Considering the limits of translation quality, it is hard to deal with machine translation errors in MT-mediated communication, even without considering the complex individual emotion-related factors, such as cultural background [15].

In view of the fact that machine translation errors cannot be ignored, we propose to shift from the transparent-channel metaphor to the human-interpreter (agent) metaphor. The agent metaphor was originally introduced by [10], in which *interactivity* is suggested as a new goal of the machine translator. Interactivity is the machine initiated interaction among the communication participants; it represents the ability to take positive actions to improve grounding and to negotiate meaning [10, 11]. Different from the traditional metaphor of machine translation as a transparent channel, interactivity makes it clear that translation errors are to be treated as channel noise. This noise can be suppressed through the efforts of the dialog participants.

In this paper we propose an implementation of the agent metaphor to enable interactivity. Interactivity is influenced strongly by the translation environment. Most translation environments involve the translation function and the user [5]. First, we have to mention the two characteristics of complex machine translation. One is the variable quality of machine translator output. The other is that, two messages expressing the same information can have widely different translation quality by the same machine translator. Second, in the transparent channel metaphor, the *activeness* of the user is ignored. Activeness plays an important role in interactivity. For example, certain people get better translation results than others because they can craft expressions that suit the characteristic of that machine translator. Thus, we need careful designs to promote interactivity.

We start by examining the machine translation of task-oriented dialogs. We list the typical translation errors leading to miscommunication. By analyzing the interactivity that can eliminate those errors, we formalize the requirements of an agent for encouraging interactivity. On one hand, the agent needs to know the translation quality. On the other, the agent needs to help the dialog participants adapt to the machine translator. Furthermore, we provide details of the design of the agent metaphor, including its architecture, interaction, and functions. In order to evaluate our prototype, we conduct an experiment on the multilingual tangram arrangement task. Next, we summarize what has been learned before discussing the limitations and implications of the current design.

MACHINE TRANSLATION MEDIATED COMMUNICATION

Machine Translation Mediated Communication Task

As an example, we established several sessions of a concrete English-Chinese communication task. The goal was the *tangram arrangement* task in which an English participant instructs a Chinese participant to construct a tangram object from seven shapes. Because of the geometric shapes, the words and phrases mainly fall into the geometry domain. Google Translate[1], one of the most popular online machine translation services, was used as the machine translator.

Communication Break Because of Translation Errors

Based on the observations made during these sessions, we analyzed the communication breaks occasioned by translation errors. In one observation, due to phrase concept mistranslation, the word "square" in the geometry domain was translated into "plaza" of another domain, because the word "square" is polysemous. The machine translator just provides the everyday meaning of the word, but its true meaning depends on the task domain. In the next observation, the mistranslated sentence is an imperative sentence that requests the receiver to conduct an act ("put something someplace"). The dialog participants often describe actions in imperative sentences, such as requests and commands. Machine translators often fail to translate imperative sentences as well as declarative sentences. Another observation is the mistranslation of inconsistent phrases (see Figure 1); the abbreviated reference ("the light one") is not translated accurately, and it is unnatural to stick to exactly the same expression globally. Such inconsistency easily leads to translation errors.

Analyzing miscommunication at the phrase, sentence, and dialog level is popular in machine-mediated communication research [14, 27]. These three observations of machine translation errors are picked up according to these levels: *phrase-level*, *sentence-level*, and *dialog-level*. Table 1 shows several existing works on examining mistranslation problems, providing suggestions and strategies for improving accuracy at each level. We summarize the mistranslation found in existing works. It shows that mistranslation often happens and can lead to communication breaks.

[1]http://translate.google.com/

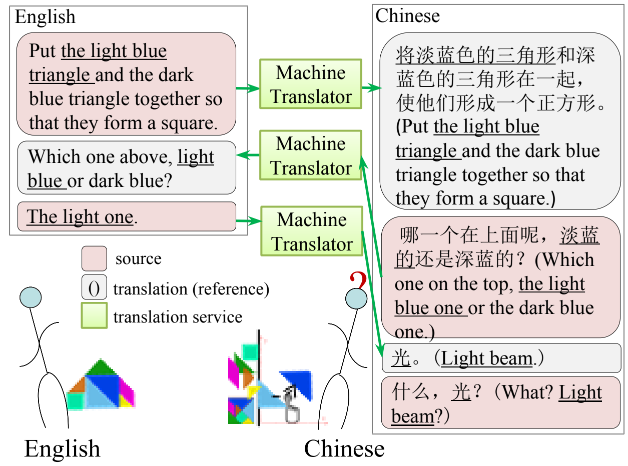

Figure 1: In English-Chinese tangram arrangement communication, the Chinese receives an inconsistent translated phrase and the communication breaks. (In this figure or following figures, the parentheses indicate references of Chinese-to-English translation.)

Level	Existing Works	Mistranslation
Phrase level	Extract and highlight inaccurate words [19], picture icons as precise translation of basic concepts [23].	Inadequate
Sentence level	Examine back-translation for sentence level accuracy check [18], Round-trip monolingual collaborative translation of sentence [7, 20].	Influent and inadequate
Dialog level	Examine asymmetries in machine translations [28], Predict misconception due to unrecognized translation errors [27].	Inconsistent

Table 1: Existing works on three levels and their corresponding mistranslation problems.

INTERACTIVITY AND AGENT METAPHOR

From Accuracy to Interactivity

When translation errors cannot be ignored in MT-mediated communication, the dialog participants can do nothing according to the transparent channel metaphor of machine translation (see Figure 1). The responses open to the machine translator fail to guarantee accuracy. If the dialog participants are encouraged to collaborate to eliminate such translation errors, the goal of the machine translator becomes to encourage interactivity. We studied what forms of interactivity could eliminate the translation errors expected. We replace the transparent channel model by introducing three interactions to eliminate translation errors (see Figures 2, 3, 4).

When translation failure is detected, the interaction process (see Figure 5) consists of: *(1)* Agent's effort to determine the *feature* of current dialog, *(2)* Agent's effort to *suggest*

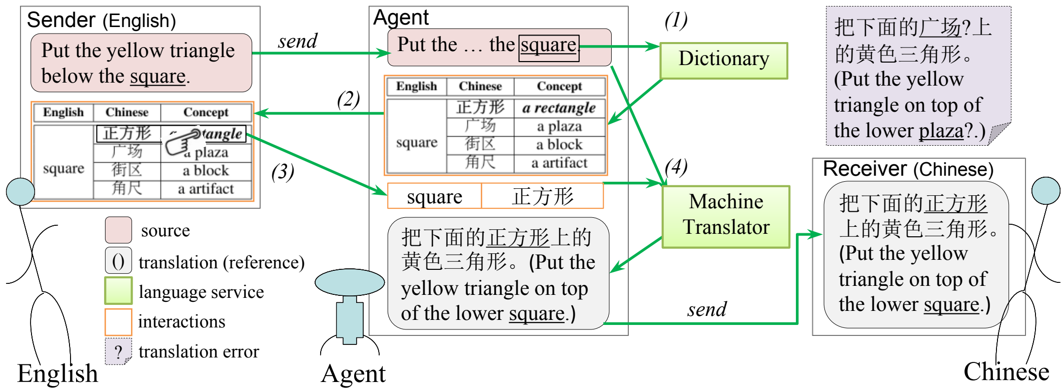

Figure 2: Interaction to handle inadequately translated phrase: *(1)* check the feature that the word, "square", has one-to-many dictionary results. *(2)* suggest the sender select the correct concept. *(3)* the sender chooses the target concept. *(4)* translate by the dictionary translator composite machine translator.

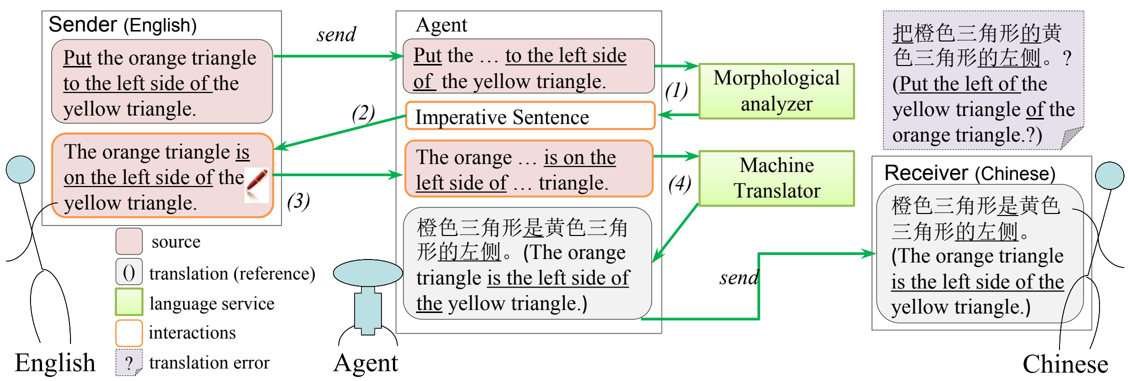

Figure 3: Interaction to handle mistranslated sentence. *(1)* check the feature that it is an imperative sentence starting with a verb. *(2)* suggest the sender rewrite the sentence into declarative version. *(3)* rewrite the sentence. *(4)* translate by the machine translator.

repair tips to the sender. Here, the human effort is referred to as "repair" as per machine translation mediated communication [11, 19]. *(3)* Sender's effort to repair the failure. *(4)* Agent's effort to translate the repaired message, and output an acceptable translation result. Given that there are multiple repair strategies, the agent has to decide the cause of the failure, send the appropriate repair suggestion to the sender. Other types of repair strategies, such as selecting phrases based on the prediction of available information [5], rephrasing based on back-translation results and sentence rewriting [19], can also be used.

Obviously, if the agent can initiate a proper interactivity with dialog participants, most translation errors can be eliminated. Still, we have to mention that the sensibility of dialog participants does not necessarily lead to the elimination of translation errors, because of the unpredictability of the machine translation function, and the uncertainty of the human repair action. Thus, the interactivity between the agent and dialog participants must be carefully designed to motivate participants by making their actions easy, even for monolingual neophytes.

Agent Metaphor for Interactivity

Our case study showed that interactivity can eliminate most translation errors. Here, we discuss why the agent metaphor is needed to establish such interactivity. Basically, there are two reasons for applying the agent metaphor: agent sophistication, and the role of the agent [13]. In this study, the agent metaphor offers *flexible autonomous behavior* and a *decision support function*.

Flexible Autonomous Behavior: Because MT-mediated communication requires online translation and interactivity, a proactive agent has the ability to avoid unnecessary operations. For example, process protocol based collaborative translation [8, 20] will go through the complete preset process flow, which is potentially inefficient. An agent enables flexible autonomous behavior, which is much more efficient.

Decision Support Functionality: Interaction will be triggered when translation errors are detected. After that, many decisions, such as translation error candidates, repair suggestions or extra translation improvement actions, need decision support functionality. A simple premise of this decision can be drawn from current translation quality. Through further design enhancement, the agent metaphor will gather additional

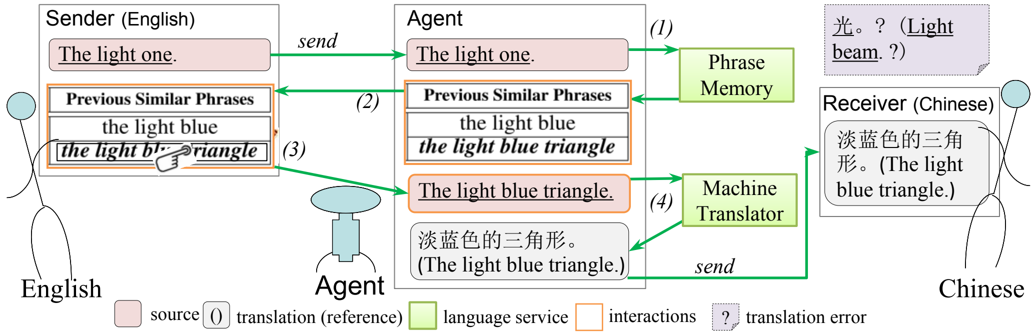

Figure 4: Interaction to handle inconsistently translated phrase. *(1)* check the feature of similar phrases existing in previous dialog. *(2)* suggest selection of appropriate previous phrase. *(3)* choose a replacement of the previous phrase. *(4)* translate by the machine translator.

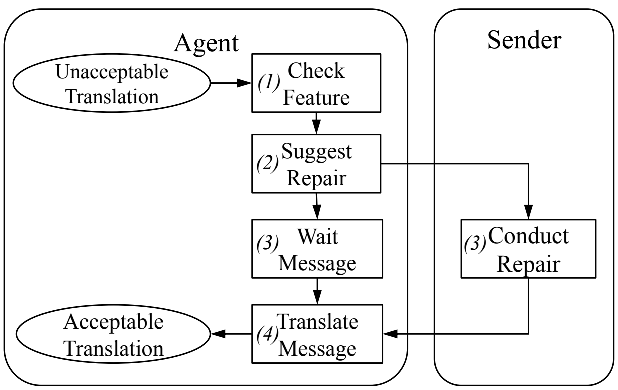

Figure 5: Four steps of the interaction process for one repair strategy: *(1)* Check Feature, *(2)* Suggest Repair, *(3)* Wait Message (Agent), Conduct Repair (Sender), and *(4)* Translate Message.

quality estimates or information from the participants. Thus, the agent metaphor has to sense the quality of current translations, build common consensus among dialog participants, and pass proper repair suggestions to participants.

DESIGN OF AGENT

Architecture

Our translation agent is designed around three agent phases: observation, decision, and action (see Figure 6).

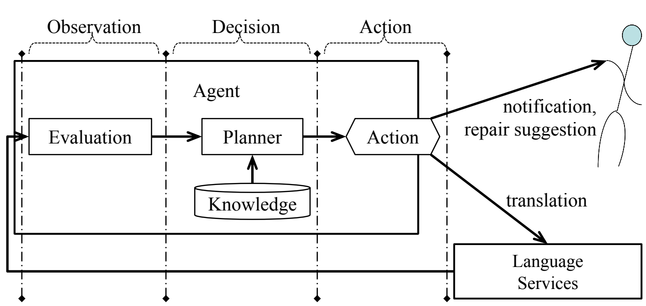

Figure 6: Architecture design of translation agent.

Observation Phase

The goal is to discern the translation quality of each message. An *evaluation* module will fill this role. Popular evaluation methods such as BLEU [21], METEOR [2], compare the lexical similarity between the translation result and a standard reference to calculate an evaluation score. Other quality estimation approaches, such as the set of quality features [24] can be considered. Previous studies use back-translation to predict potential translation errors [8, 18, 19, 20]. In this paper, back-translation and the BLEU method (maximum 3-gram, smoothed) are used as a simple way to trigger interaction.

Decision Phase

This phrase decides the actions to be taken. Here, a real time *planner* is necessary, and a knowledge base is needed to keep experience and/or policy. The planner is critical to establishing autonomous behavior and decision support. Two important facts should be mentioned here. One is that the agent needs the ability to process the dialog in real time. The other is that the activities of the dialog participants will provide uncertain results. This is because the participants might have limited ability to generate correct repair actions or the machine translation quality of each message is unpredictable. Accordingly, the planner should provide online planning and decision support to counter this uncertainty. The knowledge base will save and allow access to experience and policy.

Action Phase

Three types of actions are needed. First, to help the dialog participants get an idea of current quality, a *notification* action is needed. Second, the detection of an unacceptable translation triggers the *repair suggestion* action. The repair suggestion is the key to interactivity. Last, translation actions are needed to implement the different repair strategies.

For the actions of notification and repair suggestion, the demand is that the agent and dialog participants talk. We use a simple meta-dialog for this purpose. For the translation actions, the repair strategies in the observations of the last section require the dictionary service result, and the dictionary translator composition service (see Figure 2). These services will be provided through the Language Grid, a service-oriented platform [12]. Through Language Grid, several categories of atomic language services are available, including dictionary, parallel text, morphological analyzer, dependency parser, machine translators, etc. Meanwhile, several composite services are available, including dictionary-translator composite translation, multi-hop machine translation, and back-translation. Language Grid also provides a client that supports the invocation of both atomic and composite language services. People can develop their own version of services based on this client using Java programs. Language Grid platform support allows translation actions to be realized and invoked flexibly.

Autonomous Behavior and Decision Support

Sharing the status of translation quality between participants, and helping participants adapt to machine translation, are two goals of interactivity. Each communication dialog consists of many rounds of message transfer from one participant to the other. Through this transfer, the agent triggers interactivity. There are two message transfer states: *Acceptable* accuracy, and *Unacceptable* accuracy. If the former, after the message is translated into the other language, and the accuracy is accepted, the translated message is sent to the receiver. If the latter, the agent will notify the participants and pass repair tips to the sender who then repairs the message. The message will be sent to the agent again, and the message transfer process repeats.

Second, two interactivity goals should be met. Satisfying the first goal, sharing the status of translation quality between participants, is obvious. In the above Unacceptable accuracy situation, an informational meta-dialog will be triggered and a notification meta-dialog message will be sent to the sender. A decision on whether it is acceptable or unacceptable is needed. For the second goal, helping participants adapt to machine translation, achieving the goal is essential. Based on the previous case study of interactivity, we learned three points. The first point is that there is more than one repair strategy. This means that the agent has to decide which strategy should be taken. The second point is that repair is a four-step process {*feature*, *suggest*, *wait*, *translate*}. The third point is that the effect of any repair action is uncertain. The decision, deciding which repair strategy is to be selected under uncertainty, is especially important.

The agent has to decide whether to pass the message to the receiver, and if not, which repair strategy is to be taken. When the message is received, translated, and evaluated, the evaluation score is calculated via back-translation. The evaluation score determines whether the message is passed on or a repair strategy is needed. About the next decision, which repair strategy to adopt, the features of multiple repair strategies are checked and one is selected. These decision requirements can be met through a utility decision model [4]. The agent's autonomous behavior and decision support allow it to issue the appropriate repair strategy even under uncertainty.

Repair Strategy Example

An example of issuing the repair strategy "split", is explained. Here, we picked one rule from the AECMA Simplified English Standard [1], which is for technical manual preparation, and tried using it as the basis of a repair strategy, because simplified writing is effective in enhancing machine translation quality according to Pym's study [22].

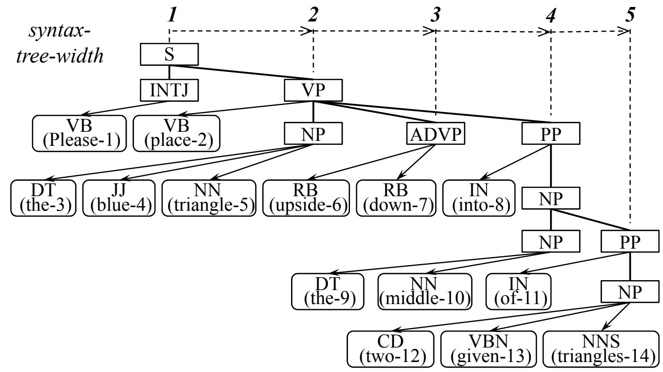

Figure 7: The *syntax-tree-width* feature of the repair strategy *split*: a width of non-leaf part of its constituency structure tree.

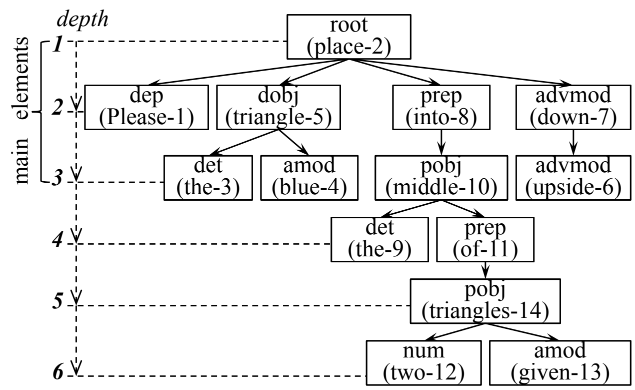

Figure 8: The *tips* for the repair strategy *split*: the core of the message, which is the main elements of the sentence with low depth (less than 4) in the dependency structure tree.

Simplified Writing Rule: use short sentences. Restrict sentence length to no more than 20 words (procedural sentences) or 25 words (descriptive sentences). Inspired by this rule, we developed the repair strategy "split". *Repair Strategy Split*: when an unacceptable translation is detected, if the message is a long and complex sentence, the repair tip is to split the source sentence into two sentences. *Feature of Split Strategy*: the literal length of the sentence is not directly used here. Instead, we choose the syntax-tree-width of its non-leaf syntax tree (see Figure 7). For example, the English message from the tangram arrange task, "Please place the blue triangle upside down into the middle of two given triangles.", is parsed into a constituency structure tree. The non-leaf part nodes form a non-leaf syntax, and its width is 5. Compared to the literal message length, this syntax-tree-width better represents the complexity of sentence structure.

Repair Suggestion: the tips are provided to help the sender undertake the repair. In this repair strategy, the core of the message, which is the main elements of the sentence with low

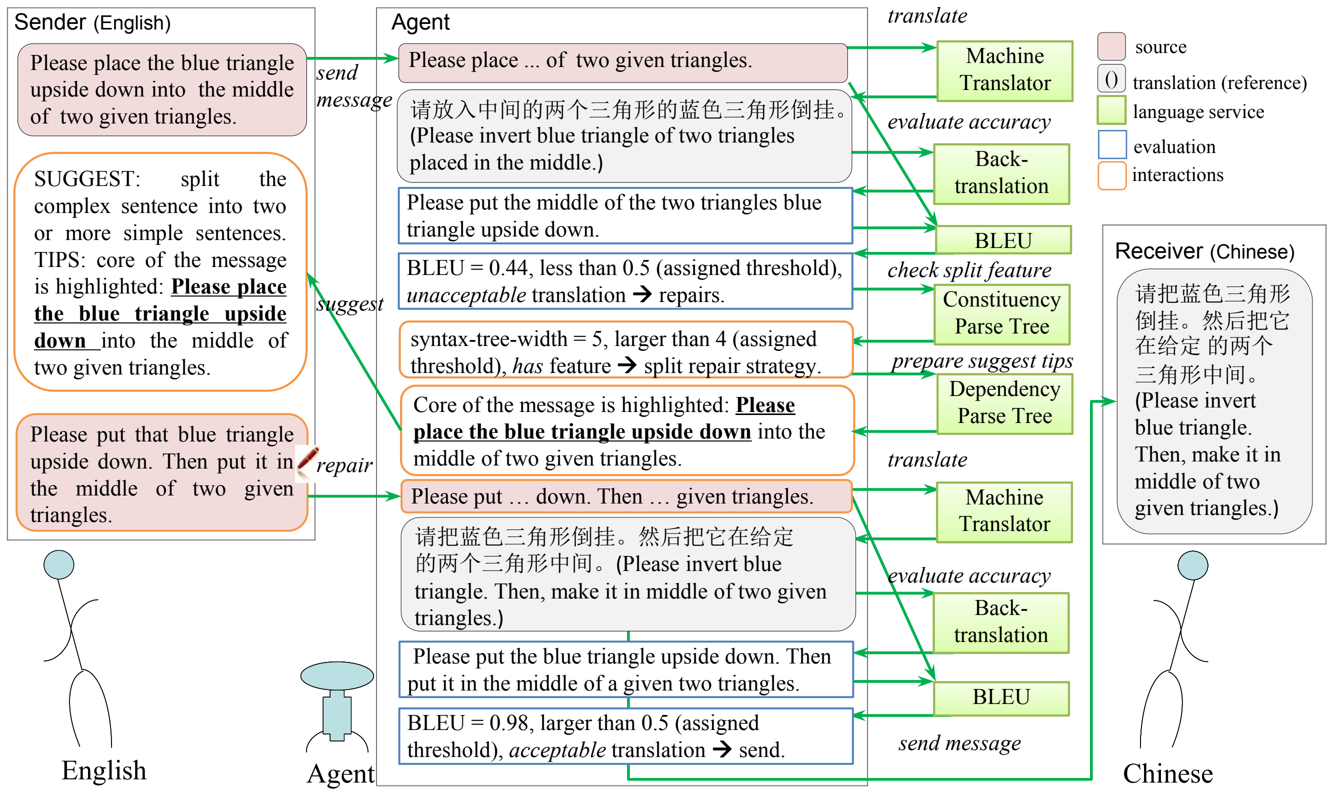

Figure 9: Example of agent's split strategy. Agent will follow the decision of sending message to receiver or starting repair strategy. Back-translation and BLEU evaluate translation quality (*accuracy*). The process steps of the repair strategy (see Figure 5) are given: check split feature, *the syntax-tree-width* (see Figure 7); suggest split with tips, *the core of the message* (see Figure 8); human repair; and translate the repaired message. Then, the evaluation shows that it becomes accepted.

depth (less than 3) in the dependency structure tree, is picked out for the sender (see Figure 8). This meta-dialog shows that, if the repair strategy is "split", then the suggestion and repair tips are passed to the sender (see Figure 9). The priority value is 0.5. It means that this will be the first message shown to the sender, if there is no higher priority meta-dialog defined for the IF premise. Both the constituency parse tree and dependency parse tree are from Stanford Parser [16], which is an open source Java implementation of natural language parsers. It provides a consistent interface for dependent parsers for English, Chinese, Arab, and German.

Here we describe the process of preparing our split repair strategy. According to our observation of the English-Chinese tangram arrangement sessions, we found instances in which this repair strategy was needed (see Figure 9). Obviously, the translated message is initially evaluated as unacceptable. We use the back-translation, the BLEU score, and the threshold for a simple decision. The usage of back-translation has been discussed a lot [8, 18, 19, 20]. The interaction process of split strategy is given and its result is shown (see Figure 9). The agent checks the feature of split strategy, prepares the suggestion tips, and feeds back the split suggestion. After the sender splits the message following the tips, the translation is evaluated again and it becomes accepted.

EVALUATION

Evaluation Methods

In order to evaluate the impact of the agent on interactivity, we conducted a controlled experiment, which compared the machine translator mediated transparent channel approach to the proposed agent mediated interactivity approach.

The Number of Human Messages per Turn Unit

We considered how the elimination of translation errors raised the efficiency of communication. Higher efficiency means that the information is transferred with fewer messages. According to conversation analysis [6], the *turn* is the basic unit interaction in the communication. Here, the tangram arrangement task can be divided into seven subtasks; there are seven pieces to be arranged. For each arrangement, the information transferred per turn unit, includes piece, rotation type, and position. The *number of human messages per turn unit* is defined as the number of messages sent by the human participants during one turn unit of the multilingual communication. It reflects the participants' effort to transfer the task information. For better data collection, after one message is sent, the participants were asked to wait for feedback before issuing the next message.

Normally, a turn unit consists of 2 messages: 1 information message from the sender and 1 feedback message from the receiver. Here, to transfer the square's position information, 4 messages are needed (the number of human messages is 4) because the translation error misleads the message receiver, and the receiver has a query. It should be noted that, in the agent metaphor, the repaired message from the sender is counted, for example, the number of human messages in the turn unit is 2 (two messages from the English sender) in the split strategy example (see Figure 9).

Experiment Preparation

An English-Chinese tangram arrangement communication task was conducted: an English user instructs a Chinese user how to arrange a tangram (see Figure 10). When the tangram is complex, this task is generally difficult to finish through text based messages, even for two native speakers. We set two limitations to make this task easier to finish. *Only use convex figures*[2]: there are only 13 convex figures. It is much easier to construct a convex figure. *Share initial state of tangram pieces*: both participants start with the same piece arrangement. With these two limitations, tangram arrangement focuses on communication.

Participants

For each tangram, we conducted the task using a single machine translator, a translation agent prototype, and bilingual translators. We randomly selected 5 tangram figures from the 13 convex figures. Two English and 2 Chinese participants, and 1 English-Chinese bilingual joined this experiment.

Repair Strategies for Agent Prototype

In this experiment the agent prototype knew three repair strategies; the *split* strategy of the last section, and the two repair strategies of Figure 2 and Figure 3: *phrase* and *rewrite*.

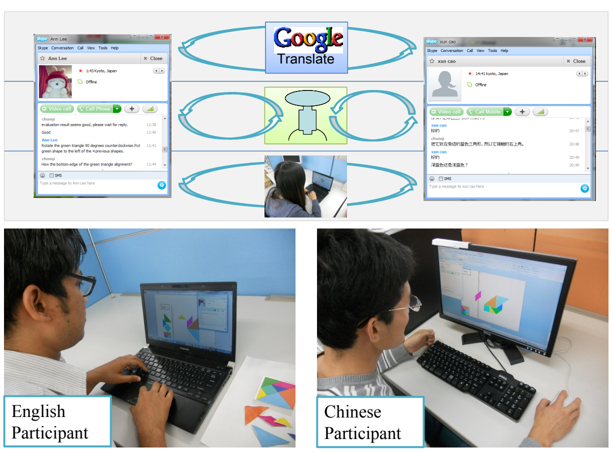

Figure 10: Experiment of English-Chinese (E-and-C) tangram arrangement through machine translator (MT), agent prototype using the wizard of OZ (Agent), and human bilingual (Human). There are two groups participants, E_1-and-C_1 and E_2-and-C_2 for this tangram arrangement experiment.

Result and Analysis

Each group was asked to finish 5 figures. The number of human messages and the average number of human messages in each turn were collected (see Table 2). The average number of human messages in each turn in human-mediated communication is 2.2. This shows that human-mediated communication is pretty efficient. The average number of human messages in each turn in machine translator mediated communication was 3.7. This shows that using machine translation almost doubles the participants' effort. Our prototype agent held the average number of human messages in each turn to 2.9, a **21.6%** improvement in communication efficiency.

Next, the total number of repair strategies in the English-Chinese dialogs was determined (see Table 3). First, the two different message senders had different repair strategies. Sender E_2's messages triggered more repair suggestions. The phrase and split strategies were used to almost the same extent. Second, different repair strategies took different amounts of time to complete. Here, the phrase strategy and split strategy were not activated as frequently as rewrite. This might be because there were few polysemous words, and the sentence structures were not too complex. We note that the senders used many imperative messages in the first instance.

Medium	Average Number of Human Messages		Average Number of Human Messages / Turn
	E_1-and-C_1	E_2-and-C_2	
MT	26.0	25.2	3.7
Agent	20.2	19.8	2.9
Human	15.6	14.8	2.2

Table 2: The average number of human messages and the average number of human messages in each turn unit for the 5 English-Chinese communication tasks.

Sender	Total Times of the Repair Strategies		
	Phrase	Rewrite	Split
E_1	6	21	9
E_2	5	17	10

Table 3: The total times of the repair strategies.

CONCLUSION

Implementing the agent metaphor proposed herein represents a paradigm shift to using interactivity to eliminate translation errors in machine-translation-mediated communication. We examined the translation errors found in the dialogs of multilingual communication, and showed that interactivity could support the dialog participants in eliminating translation errors efficiently. Thus, our goals were to create a consensus as to the current translation state and provide repair suggestions to the sender. Both are realized by our agent metaphor. Evaluation of translation accuracy is critical for the agent to determine the current translation state. Back-translation and automatic evaluation methods, such as BLEU, are used to evaluate accuracy. To realize the autonomous agent mechanism, the process of repair suggestion was analyzed, the situations of message transfer were described, and decision dependency was analyzed for autonomous behavior and decision support. Our agent uses decision-theoretic planning to make online decisions under uncertainty. Finally, we described our experiments on a tangram arrangement task with English-Chinese

[2] http://en.wikipedia.org/wiki/Tangram

task-oriented communication. The results showed that our agent prototype improved communication efficiency in the face of translation errors. The agent does help dialog participants raise the accuracy of translated messages.

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