Communication Protocol Model for Language Game with Multi-Agents and Multi-Languages Using Dynamic Radius of SOM

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Abstract - **This paper demonstrates how autonomous systems can learn and communicate with each other in three different humane languages. In this work, we proposed a conceptual model based on Language Games and Conceptual Spaces including a special technique: an optimum dynamic radius of Self-Organizing Map (SOM) for the best searching unit between autonomous agents. Our proposed model shows the visualized simulation of the potential ways of a communication protocol during Language Game. Later the performance of the dynamic and the fixed radius of SOM technique is compared and evaluated. The results show that the proposed model enhanced with the optimum of the dynamic radius at the size of 30 can outperform the standard SOM. Finally, we have shown the effects of the number of the players and the number of the topics against the success rate could reduce concept searching process, and helping autonomous learning faster and convergence matching all three languages.**

Keywords - **Language Games, Conceptual Space, Self-Organizing Map, Multi-Language, Dynamic Radius**

I. INTRODUCTION

Language Game was originally introduced by Ludwig Wittgenstein [1] as a concept mapping an object reality to a language where a speaker utters a word associated with an object, and a listener can infer that object. The notion of Language Game is long used in cognitive science, particularly in artificial intelligence (AI) since Luc Steels [2], the pioneer, introduced the work of robotics on the grounds of Language Game and many other types of research continuing until now [3-8]. It is unclear whether nowadays AI autonomous systems i.e. intelligence agents can totally learn and communicate in as complicated a way as natural human languages. However, this research area also still inspires many scientists to expose their new principles and techniques to form human concept models for autonomous agents, since most of the applications of AI interact with the human need to understand via natural human language. Nevertheless, many research studies based on Language Game have claimed how autonomous agents communicate in the way of human concepts. As such [9], Language Games and Conceptual Spaces theory [10] are used to simulate meaning negotiation in multi-agents, while other research [11-12] combining prototype [13] and random set theory [14] study a formalization of concepts based on human concept use. However, it is said that there are many approaches that utilize the combination techniques based on Language Game and Conceptual Spaces in which those research studies have not been clarified here.

According to previous works [9], in the simplified version of the Language Games, agents perform pairwise games by communicating only in English in order to reach agreement on the name to assign to a single object. In this work, we propose an extension of a conceptual model framework, which is based on Language Games and Self-Organizing Map neural networks [15] with a dynamic radius for multi-language communicative interactions between autonomous agents. The communication protocol is provided in three different languages: Thai, Chinese, and English. We assume that each agent has their own mother tongue or first language according to their parents' nationality. As a human, a child expects to inherit a set of language definitions initially similar to those of their parents. Thus, they acquire knowledge of their daily physical world by interacting with their family. As a result, innate agents primarily store their primitive words in their language list. We employ this concept in our proposed model in the following sections.

II. RESEARCH OBJECTIVES

The aims of this research are: 1) to propose a communication protocol model for multi agents to learn and communicate with each other, in particular, with natural human language in three languages: Thai, English and Chinese, 2) to compare and evaluate the performance of the dynamic and the fixed radius of Self-Organizing Map technique converge the success rate of all languages learning and transferring in the multi-agent simulation framework, and 3) to investigate the effective of the number of players and the number of topics against the success rate.

III. RESEARCH METHODS

A. Language Games

In a typical Language Game, the two agents find agreements on an object and word pairing until they meet a consensus on what the object should be named. A Language Game is a communication process in a multi-agent system. Vogt and Coumans exposed in their work [16] that Language Games can be discriminated into three different styles: observational game, guessing game and selfish game. In the observational play, the speaker and the listener both know the topic of the game, such as color. The speaker utters a word denoting the subject, for instance, the name of the color. The game is successful if the listener knows the uttered word in the right meaning, but the game fails otherwise. During the guessing game, only the speaker knows the topic of the game. The speaker utters a word denoting the subject, and the listener must guess which subject the speaker means. In contrast, in the selfish game, the agent has to infer the meanings of words from their co-occurrences in different contexts or meanings. However, it is concluded that observational games and guessing games are faster than selfish games.

B. Conceptual Spaces

Conceptual Space is a metric space in which the main feature dominates on the ground of a geometrical framework for the representation of the concepts based on the number of quality dimensions. Each dimension is associated with a metrical structure that allows a way of calculating the semantic similarity among concepts by using metrical distances. The ideas are not independent of each other but can be structured into domains, for instance, shapes and colors. The main application of the theory can be applied to develop the artificial system dealing with cognitive tasks.

C. Proposed Model

In this work, the proposed model is based on Language game; an observation game is selected, and Conceptual Spaces; Self-Organizing Map with a dynamic radius is employed. In our proposed model, a concept is represented as a node of color in a conceptual map (i.e., SOM map as shown in Fig. 1). The conceptual map has three quality dimensions of red, green and blue. The distance between nodes is calculated by the Euclidian technique together with the searching technique; best-mapping unit (BMU), as part of the learning tools for the agreement process. Each node includes an array of concepts where each concept holds a single word of three different languages in a series of hash maps associated with a weight of belief.

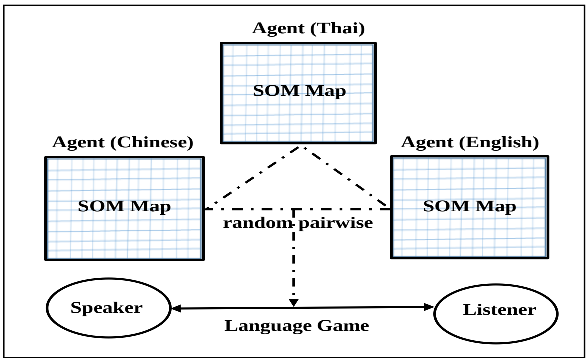

Fig. 1 Conceptual Framework

In the process of concept mappings, each agent needs to formulate an innate conceptual map with the prototypes only in the initial state. The prototypes of 10 colors of gray, blue, green, light blue, red, pink, yellow, white, black, and orange, including phonetic alphabets (Table I) of their first language (i.e., each agent was born with only one nationality) are defined to create the innate conceptual map at the beginning of the gameplay.

TABLE I
PHONETIC ALPHABETS OF TEN COLORS

Named colors in RGB formats	Thai	Chinese	English
0.25f, 0.25f, 0.25f	thea	huse	gray
0.0f, 0.0f, 1.0f	na-ngein	lan se	blue
0.0f, 1.0f, 0.0f	kheiyw	luse	green
0.0f, 1.0f, 1.0f	fa	qian-lan	light-blue
1.0f, 0.0f, 0.0f	daeng	hong	red
1.0f, 0.0f, 1.0f	chomphu	fen	pink
1.0f, 1.0f, 0.0f	lụxng	huangse	yellow
1.0f, 0.9f, 1.0f	khaw	baise	white
0.0f, 0.0f, 0.0f	dam	heise	black
1.0f, 0.25f, 0.0f	som	chengzi	orange

The SOM forms a conceptual map that is a repository of the physical world (the colors) for the internal cognition of the agent with a weight of belief in the association between the lexicon and the conceptual map. The concept's belief is an integer value from 0 to 100. If a game succeeds, the belief will be increased by one, with a maximum of 100. In contrast, if a game fails, one, with a minimum of zero, decreases the belief.

Fig. 2a and 2b are instances showing the concept maps of a pairwise Thai agent and English agent in a possible game plays whether a game is a success or failure. First, the random topic is shown to the Thai speaker, the process of BMUs the search in their concepts. In this case, the word "som" is found (with belief = 55) and shown to the English listener. Later they search in the same way as the Thai speaker. In their memories, the native words (e.g., orange) is primarily stored in hash maps which are reserved to keep three languages with a belief. In a successful game, the English listener found the word "som" in their concepts; both the speaker and the listener remove other words and increase their belief (as shown in Fig. 2a); the counter belief of the Thai speaker and the English listener are 56 and 46 respectively.

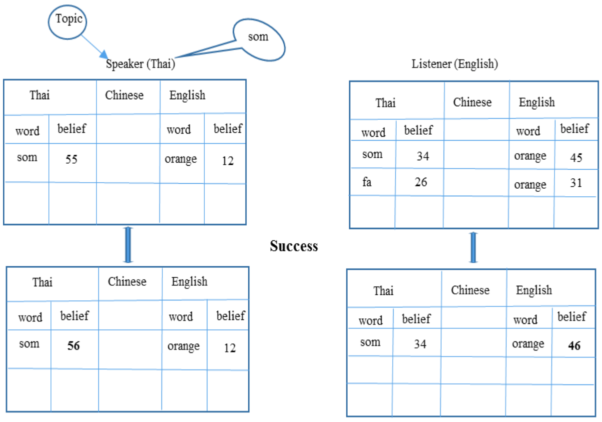

Fig. 2a Concept Maps

In a loss game, as shown in Fig. 2b, the listener updates their knowledge by adding the word "som" into their memories, and the speaker decreases their belief by one (e.g., belief = 55-1 = 54). At the same time, the listener updates their knowledge by adding the word "som", the uttered word into their memories with zero belief.

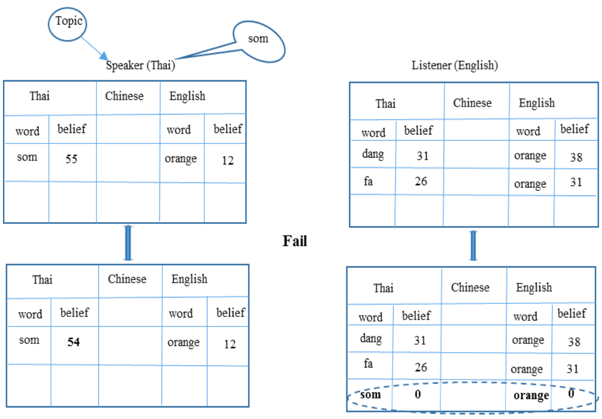

Fig. 2b Concept Maps

D. Experiments

After the SOM is trained 1,000 times with prototypes, a random topic (in a color vector) is shown to the speaker and the listener. The process of searching for the best words is undertaken; the speaker first examines in their memory, which is stored as a hash collection. If the speaker finds the mapping node in this group, they keep this word and associate it with the node. For effective communication, the speaker will search for a word within radius R in their SOM. This radius is set to fixed (e.g. r = 10, 20, 30, and 40) and expanded (e.g., r += 0.2f; 0< r < 40.0f) until the speaker can find a word in the SOM map, and is mapped as the best-matching unit, so-called BMU. This node may contain many concepts. Each concept stores a word associated with the word's beliefs. Noticeably, a counter defines the weight of expectation; each time the game succeeds, the weight is increased by one. Therefore, the word is sorted by the weight of belief.

Later the speaker utters this word to the listener as the topic that was shown to the speaker is also shown to the listener. The listener performs searching in the same way as the speaker does in their BMUs. If the listener finds this word, the game is considered successful and other words are removed from their memory. If the listener cannot find a word, the game is unsuccessful. The listener must add the speaker's word to their BMUs and the speaker decreases their belief counter by one for this word. In case of a successful game, the speaker and listener add their belief counters for that word by one.

During the proposed model simulation, SOM is considered an artificial neural network model of the brain. In the artificial brain, there is a conceptual space represented in two dimensions of SOM maps. Each SOM map consists of 24 x 24 nodes for simulated protocol communication in which each pair of speaker-agent and listener-agent learn and transfer their words in their languages. Fig. 3a-3c are instances, showing the SOM maps and lexicons of a possible agent in three languages: Thai, Chinese, and English.

Fig. 3a SOM Map in Thai Language

Fig. 3b SOM Map in Chinese Language

Fig. 3c SOM Map in English Language

It is noted that SOM map of each agent has a different form of nodes which is akin to the form of the human brain: each one is different. In this work, the simulation of SOM maps demonstrates a clear picture of node mapping in three languages on cloned SOM maps, in which there is one language per map separation. However, all agents have the same number of clusters under the influence of prototypes, i.e., clustering in ten colors.

E. Evaluation

The success rate indicates the effectiveness of the communication protocol of the proposed model. The formula, based on moving average approach, is used for evaluating the performance, and is calculated every 10 games after the listener finishes searching for a word as follows:

$$\text{Success Rate} = \frac{1}{m}\sum_{i=0}^{m}\left(\frac{1}{n}\sum_{j=t-n+1}^{t} x_j\right)_i$$

where x_j is the number of successful communications evaluated after every 10 games, n is the number of sliding windows, m is the total number of agents, and t is the number of games.

IV. RESULTS AND DISCUSSION

Autonomous knowledge sharing with multi-agents and in multi-languages is a challenging problem. We analyzed the comparative performance of a pair-wise agent on the effects of the fixed and dynamic radius of SOM when the number of topics and the number of gameplays is constant at 50 and 1000 respectively. The average of the success rate of 20 rounds of the 1000 gameplays in all languages is calculated in each size of the fixed radius (e.g., fixed radius = 10, 20, 30, and dynamic radius = 30) as shown in Fig. 4. The chart shows that the larger the radius-size the higher the rate of success. It is noted that the radius-size is optimum at 30 from our experiments (which is not shown here). However, as we mentioned before, the optimum of the radius-size of the fixed radius; the value of 30 yields faster and higher success rate than the radius-size of 10 and 20. Meanwhile the success rate of the dynamic radius (e.g., radius-size starts from 1 to 30) reaches agreement slightly faster and higher over the same size of the fixed radius over 1000 games. This is proof that our special technique, the dynamic radius of SOM is more powerful, as it can cover all the entire range for the best searching technique. In addition, we also investigate the effectiveness of the number of players and the number of topics as to the success rate. Contrary to the larger radius-size, there are fewer players; 30 players give rise of the success rate over the 50 players through 3000 games as depicted in Fig. 5. Decreasing with the number of the players, the number of topics gets smaller (e.g., 10 topics) affects the reaches of agreement better than the bigger number (e.g., 30 topics and 50 topics) during 500 games, and then stabilizes at the highest level (i.e., 100% of success rate) as displayed on Fig. 6.

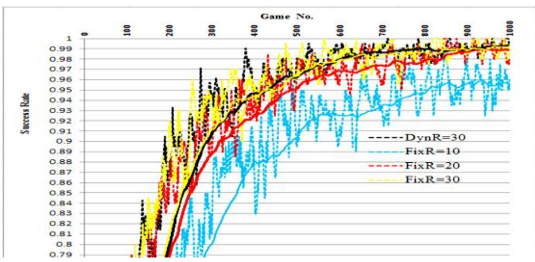

Fig. 4 Fixed Radius vs Dynamic Radius

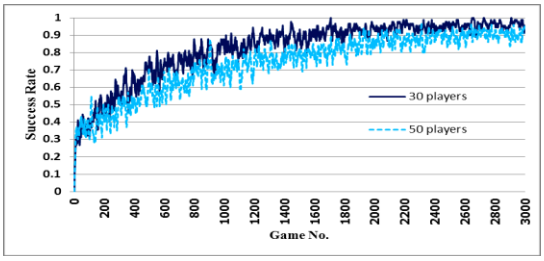

Fig. 5 Number of Players Variation

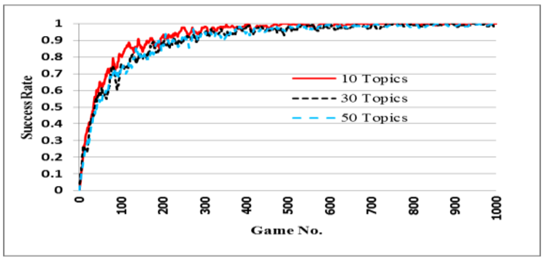

Fig. 6 Number of Topics Variation

V. CONCLUSIONS

The contribution of this paper is the proposition of a simulation framework: a communication protocol model, in order to ground the symbols used during multi-language interactions between autonomous agents. To achieve that, our proposed model uses a Self-organizing Map with a dynamic radius technique based on the Conceptual Spaces approach and the notion of Language Game. We have shown the standard approach of the fixed radius of SOM in various sizes, and compared more on the optimum value of the fixed radius against the dynamic radius; in which each size of these radiuses affects the way in which final convergence of the success rate is reached. The evaluation results showed that the optimum size of dynamic radius at 30 of SOM yield faster and higher convergence to reach the agreement, while the value of the fixed radius has significant effects on the agreement in a different level. In conclusion, our proposed model with special technique; the dynamic radius of SOM can outperform the standard SOM. Finally, we have shown the other factors that affect the success rate; the number of the players and the number of the topics, could reduce concept searching process, and helping autonomous learning faster and more effective.

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(Arranged in the order of citation in the same fashion as the case of Footnotes.)

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