THE ROLE OF CULTURAL TRANSMISSION IN INTENTION SHARING

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This paper presents a simulation study exploring the role of cultural transmission in intention sharing (the ability to establish shared intentions in communications). This ability has been argued to be human-unique, and the lack of it has deprived animals of the possibility of developing human language. Our simulation results show that the adequate level of this ability to trigger a communal language is not very high, and that cultural transmission can indirectly optimize the average level of this ability in the population. This work extends the current discussion on the human-uniqueness of some language-related abilities, and provides better understanding on the role of cultural transmission in language evolution.

1. Introduction

Language evolution is a fascinating topic in the interdisciplinary scientific community. Many empirical and theoretical studies (e.g., Oller & Griebel, 2000) have revealed a "*mosaic*" fashion of language evolution (Wang 1982) with a number of competences (e.g., social cognition, vocal tract control, imitation, etc.) all taking part in this process. There is an ongoing discussion on whether language results from abrupt changes of these abilities through macro-mutations (Pinker & Bloom, 1990), or it is caused by a quantitative evolution of "prototypes" of these abilities (Elman, 2005; Ke et al., 2006).

Among these various abilities, *intention sharing* is crucial for developing a communication system. An *intention* is a plan of action that an organism chooses and commits itself to for pursuing a goal, and sharing intentions can be viewed as intentional (selective) comprehension during interactions (Tomasello et al., 2005). Comparative studies between chimpanzees and human infants have shown that the latter ones are good at establishing shared intentions during interactions with peers or adults, while the formers are poor at it (*ibid*). Based on these findings, Tomasello and his colleagues (*ibid*) argued that sharing intentionality must be human-unique, and the lack of it in animals prevents them from developing language. However, a significant difference between modern humans and chimpanzees in this ability is insufficient to indicate the uniqueness of this ability to humans, since it may result from a gradual evolution along with the development of the human communication system. Apart from comparative studies, we therefore need other methodologies to investigate its development in humans. Computational simulation is efficient in this respect, and has been widely adopted to tackle problems concerning the evolution of language and other cognitive activities (e.g., Cangelosi et al., 2006).

This paper presents a simulation study to explore intention sharing and some possible forces to adjust its level which is quantified as the probability of establishing a shared intention during communications. We argue first that the adequate level of this ability to trigger a communal language need not be very high, and that a small quantitative change of it can greatly affect the understandability of the emergent language. Second, cultural transmission can help to optimize the level of this ability in the population to "assist" language emergence. A low level of it can be increased, while a high level can be slightly reduced. Third, the emergence of *displacement* (human language can efficiently describe the events not occurring in the immediate environment of the conversation, Hockett, 1960) in human language could be a side effect of the optimization role of cultural transmission in intention sharing.

The rest of the paper is organized as follows: Section 2 roughly reviews the adopted language emergence model; Section 3 introduces the framework to explore the role of cultural transmission in intention sharing; Section 4 discusses the simulation results; and finally, Section 5 provides the conclusions.

2. A brief Review of the Language Emergence Model

The adopted model in this paper was originally designed to study the coevolution of compositionality (in the form of lexical items) and regularity (in the form of word order) during language origin (Gong et al., 2005; Gong, 2008). Its conceptual framework is shown in Fig. 1, in which utterances encoding simple integrated expressions such as "run<fox>" (meaning "a fox is running") or "chase<wolf, sheep>" (meaning "a wolf is chasing a sheep") are exchanged among agents during communicative acts. Through the pattern extraction ability, individuals may acquire some recurrent patterns in the exchanged utterances as lexical items (see the LEXICON rectangle in Fig. 1). By sequential learning, individuals may acquire local orders recording order relations among two lexical items in the exchanged utterances. In addition, when individuals observe that some lexical items with the same semantic role are *similarly used* (display the same local order with respect to other lexical items) in some exchanged utterances, they can assign these lexical items to the same category; for simplicity, we labeled them with the syntactic roles met in simple declarative sentences in English (‘S’, Subject; ‘V’, Verb; and ‘O’, Object). Through reiterating local orders among categories, individuals gradually acquire emergent global order(s) to regulate strings of lexical items from categories and form utterances to encode integrated meanings. For instance, if an individual’s linguistic knowledge includes some S, V, and O categories locally ordered “S before V” and “O after V” that lead to an emergent global order SVO, then, he/she can express the integrated meaning "chase<wolf, sheep>" as /WOLF CHASE SHEEP/, letters within “/ /” are utterance syllables chosen from a signaling space and not necessarily identical to English words. The initial stage of the model could be either no language at all or a small holistic signaling system in which all individuals share a small number of holistic rules to encode some integrated meanings. Through iterated communications, a compositional language having a set of lexical items and global order(s) gradually emerges. This model gives us an appropriate level of complexity to observe the effect of intention sharing on language evolution and the optimization role of cultural transmission in adjusting the level of this ability.

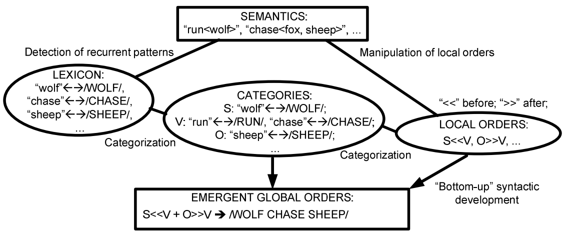


Figure 1. The conceptual framework of the language emergence model: the SEMANTICS rectangle stands for the predefined semantic space; the ovals represent the three aspects of linguistic knowledge acquired by agents based on different domain-general abilities: pattern extraction, sequential learning, and categorization; the EMERGENT GLOBAL ORDERS rectangle encompasses the emergent syntactic patterns triggered by this linguistic knowledge.

Intention sharing in this model boils down to *the availability of the topic from the environment during communicative acts*, and it is simulated as an individual’s parameter, *Reliability of Cue* (*RC*), which indicates the probability (from 0.0 to 1.0) for the listener in a communication to accurately acquire the speaker’s intended integrated meaning in the heard utterance from an *environmental cue* (an ongoing event represented by an integrated meaning in their environment). In a communication without intention sharing, a wrong cue containing an event different from the speaker's intended meaning is given to the listener; in a communication with intention sharing, the speaker's intended meaning is directly given to the listener through a cue. From the speaker's perspective, *RC* indicates the probability of choosing an ongoing event in the immediate environment as the topic of the communicative act. From the listener's perspective, it indicates the probability of referring to the ongoing event to assist comprehension. If *RC* is 1.0, intention sharing is established in all communications; if it equals 0.0, the listener only gets wrong cues, and no intention sharing is established in any communication. In this paper, the relations among *RC*, language emergence, and cultural transmission are discussed by evaluating two indices: *Understanding Rate* (*UR*, the average percentage of accurately understood integrated meanings in communications of all pairs of agents in the population based on their linguistic knowledge only and without referring to cues) and *Convergence Time* (*CT*, the number of generations of communications to reach a high *UR*, say 0.8).

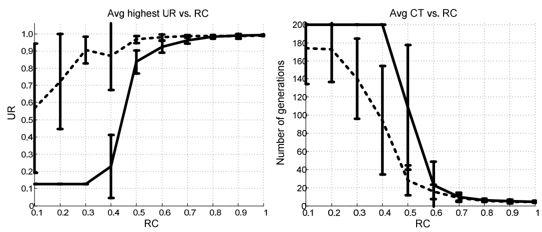
3. The Cultural Transmission Framework

Cultural transmission is defined as the communications among individuals from the same (*intra-generational*) or different (*inter-generational*) generations. As the medium of language exchange, it plays important roles in language evolution. In this paper, we assume that there is an ongoing optimization process based on linguistic understandability during cultural transmission; individuals who can better understand others in communications may obtain more resources and produce more offspring, and these offspring may maintain some of their parents' language-related abilities. A cultural transmission framework is simulated under this assumption to test whether this optimization process plays a role in adjusting *RC*. In the framework, after a number of intra-generational transmissions, some individuals who have higher linguistic understandabilities will become "parents" and produce "offspring". The offspring replicate their parents' *RC* values with some occasional, small changes. GA-like mechanism such as mutation (a tiny increase/decrease in a *RC* value) is applied during the reproduction. After "birth", the offspring start to learn from their parents through inter-generational transmissions, and then replace them and other individuals from the previous generation. After that, a new cycle begins. For the sake of comparison, another type of simulations without optimization is implemented, in which agents are randomly chosen as parents to produce offspring regardless of their communicative success in each generation. During the reproduction process, mutation is also applied.

In all simulations of this paper, the population has 10 agents. In the first generation, all individuals' *RC* values are randomly chosen from a Gaussian distribution of *RC* whose standard deviations are 0.01 and their means range from 0.0 to 1.0 in different conditions. In each generation, there are 200 rounds of random pairwise intra-generational transmissions and 200 rounds of inter-generational transmissions from parents to offspring. A round of transmissions includes 10 communications among different pairs of agents. After intra-generational transmissions, 5 agents are chosen as parents, each producing 2 offspring. During the reproduction process, a small (0.1) increase/decrease of the *RC* values occurs with a probability of 0.02 (the mutation rate). The total number of generations is 200. In the simulations with optimization, parents are chosen according to their linguistic understandabilities, i.e., the average percentage of integrated meanings that they, without referring to cues, can accurately understand when others speak to them. In the simulations without optimization, parents are randomly chosen. In each condition of the simulations, the results of 20 runs are collected for statistical analysis.

4. The Simulation Results

Fig. 2 (a) records the average and standard deviation values of the highest *UR* throughout the simulations in the 20 runs with different initial *RC* values. *UR* reflects the average linguistic understandability of the whole population. Fig. 2 (b) illustrates the average *CT* under different initial *RC* values.



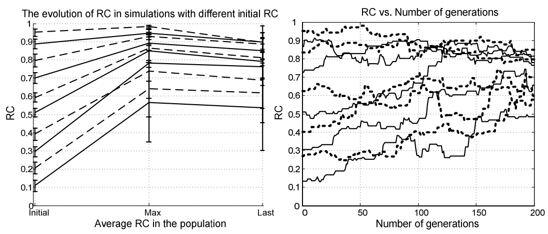
(a) (b)

Figure 2. The simulation results with and without optimization: (a) Average highest *UR* vs. *RC*; (b) Average *CT* vs. *RC*. The dashed lines trace the results with optimization during cultural transmission, and the solid ones trace the results without optimization.

In the simulations without optimization, when *RC* is low (below 0.3), *UR* is rather low (around 0.125, the *UR* of the initially shared holistic rules), and a communal language with a high *UR* does not emerge in the population; when *RC* lies in the interval [0.4 0.7], a communal language emerges, and the increase in *RC* accelerates language origin, which is indicated by the decrease in *CT*; when *RC* is rather high (over 0.8), an increase in *RC* does not further accelerate language origin. These results suggest that without optimization, a relatively low *RC* (around 0.5) is sufficient to trigger a language with a high *UR* (around 0.8), and a small increase in *RC* from 0.4 to 0.5 causes a qualitative change from no language to a communal one. In other words, a small phenotypic change can result in a communication means of a totally different nature (Elman, 2005).

In the simulations with optimization, the adequate level of *RC* to trigger a communal language is further reduced; a much smaller initial *RC* (0.2) can trigger a communal language with a high *UR* (over 0.6). In addition, language origin in these simulations is more efficient than that in the simulations without optimization. However, if the initial *RC* is high (over 0.7), language origin doesn't differ much in these two types of simulations.

The evolution of *RC* values in the simulations with optimization is shown in Fig. 3, in which Fig. 3 (a) traces the average and standard deviation values of initial, maximum and last *RC* throughout 200 generations and Fig. 3(b) traces the *RC* values in some particular runs. If the number of generations extends a little bit, say 300, a similar trend is maintained, though the further update (increasing or decreasing) of *RC* is inexplicit.



(a) (b)

Figure 3. The evolution of *RC* in the simulations with optimization: (a) Statistical results of *RC*, each line summarizes the initial, maximum and last *RC* values in the simulations with a particular range of initial *RC* (from 0.1 to 1.0 with a step of 0.1); (b) Specific *RC* values in different runs, each line records the *RC* values at different generations in one simulation.

Two roles of cultural transmission with respect to *RC* are shown in Fig. 3. The optimization during cultural transmission is based on individual linguistic understandability. Since a high *RC* contributes to the acquisition of correct linguistic rules that help an individual to accurately understand others' idiolects, it can be indirectly selected by cultural transmission, and gradually spread in the population. Then, the average level of *RC* in the population increases gradually in respond. This increasing effect is well illustrated in Fig. 3, especially when the initial *RC* is low (below 0.8). However, if the initial *RC* is already high (around 0.7), cultural transmission does not greatly change it, but maintain it throughout the simulations. For a rather high *RC* in [0.9 1.0] interval, cultural transmission may even lead to a slight reduction of it; its last value becomes slightly smaller than its initial one, as shown in Fig. 3 (a).

Slightly reducing a rather high *RC* is a side effect of optimization. Since these initial *RC* values are high enough to trigger a communal language, an individual who has a slightly lower value can still have a high understandability, and be chosen as the parent to produce offspring and spread this *RC* to the population. Then, the average level of *RC* in the population may slightly drop, without greatly affecting the *UR* of the emergent language. In this situation, there are a number of communications with no intention sharing during cultural transmission, which provides the opportunity for agents to develop robust linguistic knowledge that needs no assistance of cues or even resists distractions of wrong ones. This reliable language can efficiently describe the events not occurring in the immediate environment, gradually liberate itself from the restriction of nonlinguistic information, and become efficiently used in communications with no cues or other nonlinguistic assistance. Compared with the increasing effect on *RC*, this reducing effect is not much explicit in the short run, but it is crucial for language evolution in the long run.

5. Conclusions

The simulations in this paper demonstrate the roles of cultural transmission in intention sharing. Cultural transmission can adjust the level of this ability to trigger a communal language. Meanwhile, it can also prevent this ability from going rather high so that displacement can establish in the emergent language. Apart from shaping linguistic features such as compositionality and regularity, our study shows that cultural transmission can help to optimize some language-related abilities, leading them to optima that are not necessarily the highest possible values.

In addition, the framework in this paper can be adopted to study the role of cultural transmission in other language-related abilities, such as the ability to detect recurrent patterns or manipulate local orders. This approach will provide a clear picture on the "mosaic" fashion of language evolution, and may help to verify the claim of Connectionism (Elman, 2005) that small phenotypic changes in our species may yield language as the outcome.

Finally, the level of *RC* is modified via some GA-like mechanisms during inter-generational transmissions based on individual linguistic understandability. The adopted GA-like mechanism does not imply that the ability of intention sharing has to be updated necessarily through genetic transmission, and other optimization mechanisms may play a similar role.

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