Can Mutual Imitation Generate Open-Ended Evolution?

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Abstract

We only find open-ended evolution (OEE) in the development of human technology or in the evolution of life itself. The research on OEE at ALIFE aims to discover a mechanism that generates OEE automatically in a computer or machine. A potential mechanism and the conditions required have been discussed in three previous workshops. In this study, we propose and discuss man–machine interaction experiments as a new OEE mechanism. The pertinent definition of OEE here is whether we can continue to create new movements that are distinguishable to us. We consider the development of body movement patterns generated when Alter3 androids imitate each other and when Alter3 androids and humans imitate each other. We use UMAP contraction and transfer entropy to measure these changes and demonstrate that man–machine communication is far more dynamic and complex than the machine–machine interaction. We discuss how human subjects can engender OEE via communication with the android.

OEE in man-machine interaction

Children are geniuses at devising new ways to play and are typically always doing something different from the day before. We want to think of OEE in terms of these temporal and spatial scales: everyday life. In this study, we discuss whether mutual imitation can engender OEE. As has been intensively studied by Jacqueline Nadel, Trevarthen, and others, it is amazing to see how very creatively children communicate. In an imitation game shared by J. Nadel, one kid tried to use a bucket as a hat and the other kid mimicked his actions while laughing loudly (Nadel (2014)). The first kid then switched to playing pretend with another object, and then another. When we observe couples conversing, synchronous action is often observed; e.g., when one sips his/her coffee, the other takes a sip too. In the kids' imitation game, the kids are conscious of their actions and the other's actions. In the case of the couple, the individuals are not aware of their synchronous behaviors.

Synchronous communication, either conscious or unconscious, is inherent in human communication. From the kids' imitation game, we assume that the imitation may generate creativity. Concerning an OEE mechanism, we consider whether metacognition during communication is important for generating OEE. If the development of the brain follows a similar path as biological evolution, then metacognition during communication may be essential for generating OEE. This is what we would like to explore toward the end of this study.

Our methodology is as follows: Using humanoid robots (androids), we examine the interaction between androids, an android and a human, and human-human interaction. The androids are programmed to imitate the human/android pose in front of its eyes. The results are compared with those of the human-human and human-android interactions.

We use a newly developed android called Alter3 (Masumori et al. (2021)), which we have been developing with Hiroshi Ishiguro since 2016. Alter is an approximately 190 cm tall semi humanoid robot made of metal and motors. The Alter series has evolved from Alter1, Alter2, and Alter3 in terms of both hardware and software. The common feature is that only the upper body is motile, which includes facial expressions. Each Alter model is slightly different with respect to the number, position, and range of the axes it drives. However, they all share the same concept of emulating the movements of the human body. Each axis has an operating range of 256 steps and is driven by air pressure controlled by a computer program. For example, Alter3 has 43 axes across its entire body. The Alter3 has two eyes and is equipped with cameras in each eye, through which it can detect people in front of it and acquire their poses. It then tries to imitate that pose. However, because the body shape and the range of movement of the individual to be imitated are different, it is not possible to achieve the same pose. In this case, Alter3 remembers poses it has imitated in the past and selects one to imitate. For this study, the imitation between humanoids is done by Alter2 and Alter3 (Fig. 1). Unfortunately, Alter2's eyes are not equipped with a camera. Thus, in experiments where both Alter2 and Alter3 were used, we used fixed cameras and motion sensors placed in front of Alters body to reproduce the same condition as Alter2 and Alter3.

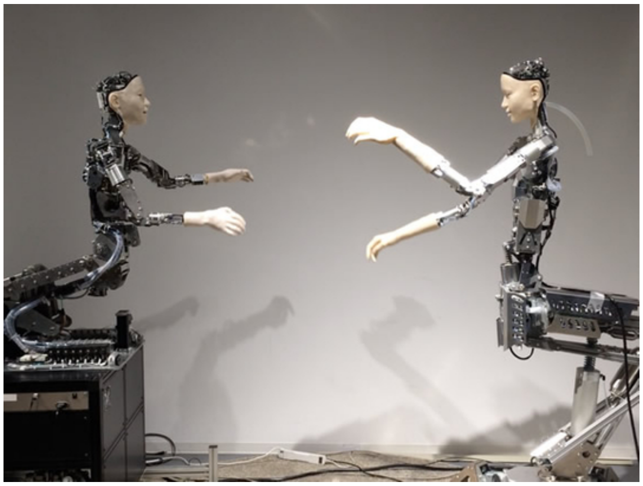

Figure 1: Example of mutual imitation between Alter2 (left) and Alter3 (right).

Autonomy by Isolated Artificial Neurons

We give micro-autonomy to Alter3 by constantly applying a *fluctuation* produced by an artificial neural network when it executes a pose. This artificial neural network is a network of 1,000 Izhikevich-type spiking neurons (Izhikevich (2003, 2004)) randomly connected to each other. From the network, 20 neurons are simultaneously applied to each joint with no overlap. More precisely, the state of these 20 neurons is normalized to the value of the output that moves each joint, and then applied. The degree to which this neural fluctuation is applied is given as a hyperparameter. Consequently, the Alter3's imitation not a perfect copy. This *copying error* is caused by: (1) physicality and (2) noise. To assess the accuracy of the imitation, we calculate the optical flow (Farnebäck (2003)) of our pose and compare it with the imitation. The optical flow is defined as the difference between the image of the opponent's pose represented by a 20×20 lattice and the image of the previous pose. The autonomy of Alter3 is characterized by two features: first, it does not stop playing when there is no opponent to imitate in front of it. In this case, Alter3 randomly selects a pose from its memory and executes it. In addition, the memorized poses can themselves be recombined with other poses in a genetic manner. In essence each pose is a gene to which Darwinian evolutionary dynamics are applied. The more poses that are selected, the more they are remembered and the more similar poses are remembered.

Alter3 extracts the skeletal structure of a person using openpose (Cao et al. (2017)) if there is a person in the image from the eye camera (or using motion sensors (Azure Kinect DK) instead of using eye cameras and openpose to extract it, for reproducing the same condition as Alter2 and Alter3. Which method was used depends on the experiment.). The skeletal structure is then transformed into the values assigned to its 43 axes and the Alter humanoid imitates the pose of the person in the eye. However, this imitation is not perfect, in part because the transformation of the image into the 43 axes is not perfect (the depth of field is not calculated properly), and partly because the Alter's body is not fully controllable and there is a time delay to that control.

Mutual Imitation Game

Mutual imitation is *play* that involves imitating each other. This play, as demonstrated by children, is very creative (Nadel (2014)). In this regard, there is an important pioneering study on imitation in mother–child interaction by Murray and Trevarthen (Murray (1985)), who later discussed the development of this communication between parent and child in relation to the intrinsic human rhythm. Alter also imitates the pose of a *person* if it sees him/her in its eyes. We consider four mutual play conditions: (1) between an Alter and a person; (2) between Alters; (3) between two Alters possessed by two different people, where possession means that the person moves the Alter's body as if it were his or her own; and (4) between an Alter and itself in a mirror.

In the second condition, the imitation between humans is done via possession of Alter3 and the Alter3's body. The procedure for possession is as follows: Using a head-mounted display (Oculus Quest2), the human subject views the image seen through the eyes of the Alter. The person's movements are simultaneously captured by the motion sensor (Azure Kinect DK), which calculates the values assigned to the 43 axes of the Alter and moves the Alter's body correspondingly. The subject would see the Alter's hand through the eyes of the Alter as if it were his or her own hand. This gives the subject a sense of agency and ownership of the Alter's hand and body. The other human subject *possesses* the other Alter in the same manner. Each subject looks through its Alter's eyes at the Alter's physical counterpart. They are then asked to perform mutual imitation.

Analysis of the Three conditions

The main analyses are performed using UMAP and transfer entropy. UMAP is a method of dimensionality reduction introduced by McInnes et al. (2018), which has excellent performance with regard to python implementation speed and facilitating data manipulation that the original data to place similar groups of data close together. We use it to trace the temporal evolution of the Alter's body movements.

Transfer entropy (TE) is a method of calculating the "upstream-downstream" comparisons of information between two or more time series (Schreiber (2000)). TE calculates whether the past of A has the most information to predict the future state of time series A, or whether the past of another time series B has the most information, in an extended form of mutual information.

The results for each condition are as follows:

(1) Interaction between a human and an Alter

An Alter switches between three modes: (i) copying the pose of the person in front of it; (ii) failing at the first mode, the Alter selects a similar pose from memory and executes it; (iii) if there is no person in front of it, the Alter randomly selects a pose from a memory array and executes the pose. When the Alter stores this pose away in the memory array, it is added to the neural noise. By computing the UMAP for mode (i) and memory mode (ii) and (iii), we can tell from the UMAP that new poses are created (Fig. 2).

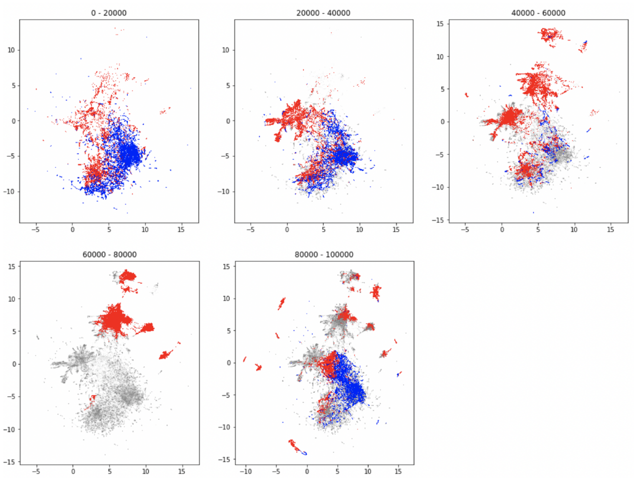

Figure 2: Example of the time development of motion patterns. Blue dots represent poses generated with pose detection algorithm. Red dots represent poses recalled from the memory. (Adapted from (Masumori et al. (2021)))

We notice that TE shows an oscillatory behavior; when an Alter is successfully imitating a person, there is an entropy flow from the person's pose to the Alter's pose. However, when the imitation fails, the person often tries to imitate the Alter's poses, and entropy flows from the Alter to the person (Masumori et al. (2021)). This is how mutual imitation arises naturally.

It is interesting that in this case, the person enters into a state of mutual imitation, even though he was not seeking to imitate. However, the imitation pattern shifts, which may explain the urge to break off the imitation if it continues for a while. Taking the UMAP of these interactions, we see that the complexity of the UMAP gradually increases. Why the UMAP keeps producing new patterns is that people update the patterns spontaneously. By playing the imitation game, Alter can store new poses in his memory array. The changes in the UMAP plotting are a reflection of the ever-changing patterns of behavior, i.e., OEE.

We also asked a human subject to try to imitate the Alter's behavior. This is a pure mutual imitation game and the UMAP generates complicated patterns step by step.

(2) Interaction between Alters

Mutual imitation between Alters did not complicate the development of the UMAP very much. This is demonstrated by computing the UMAP (Fig. 3). The obvious solution to reciprocal imitation is to remain still in the same pose (cf. Friston's paradox of the dark room [Friston et al. (2012); Froese and Ikegami (2013)]). Now, no mechanism has been introduced to explicitly exit this state. Therefore, once androids show a specific pose repeatedly and it is well imitated, it can be maintained. In particular, if they do not access a memory state, they will continuously react only to each other.

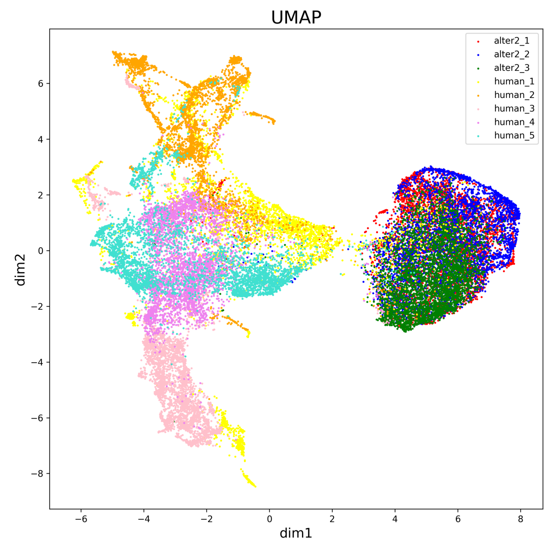

Figure 3: Motion patterns when Alter3 interacts with Alter2 and when it interacts with humans. Red, green, and blue dots represent poses when Alter3 interacts with Alter2, and other colors represent those when it interacts with humans.

However, Alters can sometimes exit fixed points. As mentioned earlier, neural fluctuations are applied to each joint when the Alter moves. The neural fluctuations are delivered by adding up the state of the neurons taken from the common neural network. This neural network is randomly coupled and has Hebb plasticity. Sometimes, all the neurons fire in the same phase and a global synchronization state occurs. This synchronous state causes large actions in the Alter, such as raising both its hands at the same time. Yet each neuronal network in each Alter are not coupled, the synchronous state occurs spontaneously by accident.

Yet the UMAP does not evolve like in the case of human–Alter interactions during which the Alter sometimes exits the fixed-point state via the synchronous firing of neurons and at least two imitating states emerge. In addition to this, Alter2 and Alter3 have different body sizes and architectures, with different degrees of freedom; thus, imitation cannot be perfect. This is another mechanism that destabilizes the fixed-point pose.

(3) Interaction between Alters possessed by humans

Imitation between human beings does not, of course, fall on fixed points or the like, and there is an impression that it proceeds slowly and explores many poses. A detailed analysis is yet to be done, but one thing we can say is that the UMAP representation can distinguish this form of imitation from the imitation between Alters driven by autonomous programs (Fig. 4).

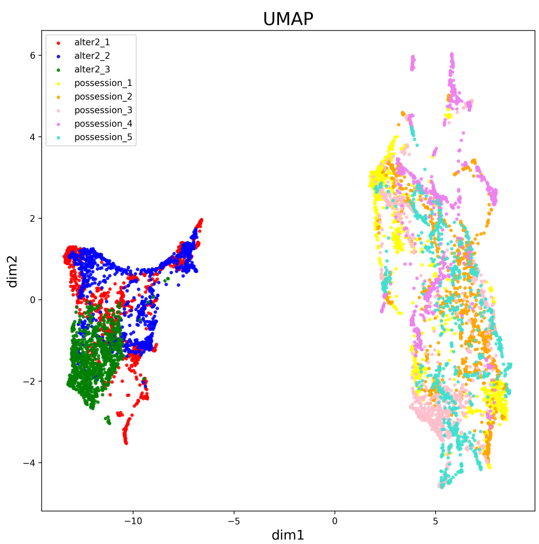

Figure 4: Motion patterns of Alter3 possessed by human and Alter3 with autonomous program. Red, green, and blue dots represent poses of autonomous Alter3 interacting with Alter2, and other colors represent poses of Alter3 possessed by human, interacting with Alter2 possessed by human.

(4) Interaction with mirrors

The image in the mirror can be imitated perfectly without any time delay as this involves the same body size and architecture. Furthermore, the pose with the hands down stabilizes immediately.

Discussions

There is a difference between the UMAP for android and human-mediated mutual imitation: The UMAP tends to become more complex when a human is involved. These experiments were conducted on a scale of 30 minutes to an hour with a small memory capacity (approx. 6 min). However, the situation may change if we use a larger memory capacity and a longer timeframe for mutual imitation. At the Barbican, there was a lengthy period when no one appeared and Alter played with his own past poses, rather than imitating these poses.

Therefore, from the experiment above, we conclude that OEE is expected when: (1) an android has a set of memories of past poses, (2) there is human interaction, and (3) there is solitary play with memory without a human in front of the Alter. In addition to these conditions, we propose that mutual imitation is required to boost behavioral creativity. Primarily, human intervention is critical because humans are autonomous creatures and possess free will. This human autonomy is a typical bottomlessness found in living systems. Tom Froese posits that this bottomlessness is essential for the emergence of OEE (Taylor et al. (2016)). Strazewski proposes the same principle: a messy system can facilitate OEE, and as such, a new degree of freedom (Strazewski (2015)). Humans can be better defined as monsters with a bottomless pit. cf. Michel Bitbol (Bitbol (2007)).

Secondly, when Alter retrieves memory, neural noise is imposed, which is very important for producing creativity. In this experiment, we used the Izhikevich model to create a closed neural network with no input, from which connections were made to each axis. The network shows spontaneous neuronal firings and global synchronization. This is what helps Alter to break out of its fixed pose. Random noise has no such synchronization. Nevertheless, a similar pattern emerges between artificial brains with a similar number of neurons and is a source of spontaneity. In this case, the interaction between Alters has led to a diversity of body movements, which often depends on this Izhikevich cell model.

One last thing we want to mention is that imitating Alter3's poses can evoke emotions. As was discussed by Wallon, imitating communication is emotional resonance (also discussed in Nadel et al. (1999)). Because it evokes emotions, an imitating game is not merely the reproducing of poses and gestures but involves the creation of new communicative ways.

Acknowledgements

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References

Bitbol, M. (2007). Ontology, matter and emergence. *Phenomenology and the Cognitive Sciences*, 6(3):293–307.

Cao, Z., Simon, T., Wei, S.-E., and Sheikh, Y. (2017). Realtime multi-person 2d pose estimation using part affinity fields. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7291–7299.

Farnebäck, G. (2003). Two-frame motion estimation based on polynomial expansion. In *Scandinavian conference on Image analysis*, pages 363–370. Springer.

Friston, K., Thornton, C., and Clark, A. (2012). Free-energy minimization and the dark-room problem. *Frontiers in Psychology*, 3:130.

Froese, T. and Ikegami, T. (2013). The brain is not an isolated "black box," nor is its goal to become one. *Behavioral and Brain Sciences*, 36(3):213–214.

Izhikevich, E. M. (2003). Simple model of spiking neurons. *IEEE Transactions on Neural Networks*, 14(6):1569–1572.

Izhikevich, E. M. (2004). Which model to use for cortical spiking neurons? *IEEE Transactions on Neural Networks*, 15(5):1063–1070.

Masumori, A., Maruyama, N., and Ikegami, T. (2021). Personogenesis through imitating human behavior in a humanoid robot "alter3". *Frontiers in Robotics and AI*, 7:165.

McInnes, L., Healy, J., and Melville, J. (2018). UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction. *ArXiv e-prints*.

Murray, L. (1985). Emotional regulations of interactions between two-month-oldsand their mothers. *Social perception in infants*, pages 177–197.

Nadel, J. (2014). *How Imitation Boosts Development: In Infancy and Autism Spectrum Disorder*. Oxford Univ Pr, Corbett, Eleanor.

Nadel, J., Carchon, I., Kervella, C., Marcelli, D., and Réserbat-Plantey, D. (1999). Expectancies for social contingency in 2-month-olds. *Developmental science*, 2(2):164–173.

Schreiber, T. (2000). Measuring Information Transfer. *Physical Review Letters*, 85(2):461–464.

Strazewski, P. (2015). Omne vivum ex vivo… omne? how to feed an inanimate evolvable chemical system so as to let it self-evolve into increased complexity and life-like behaviour. *Israel Journal of Chemistry*, 55(8):851–864.

Taylor, T., Bedau, M., Channon, A., Ackley, D., Banzhaf, W., Beslon, G., Dolson, E., Froese, T., Hickinbotham, S., Ikegami, T., et al. (2016). Open-ended evolution: Perspectives from the oee workshop in york. *Artificial life*, 22(3):408–423.