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Giving Robots a Flexible Persona: The five factor model of Artificial Personality in Action

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Abstract: A computational framework for *artificial personality* in cognitive robots is introduced. While every robot has some form of personality, the framework reported here is flexible and enables the exploration of different behaviors on the same robotic platform. The framework described here maintains a probabilistic representation of an internal state that includes emotion, motivation, sensing, and previous action. The next action is computed by using a massive number of rules implemented using Bayes Rule. This flexible Bayesian representation of personality allows the robots personality to be designed by a personality generator algorithm. The authors present results in a real robot and compare the behavior of robots with differing personalities.

Keywords: Artificial Personality, Big Five, Cognitive Robotics

1. INTRODUCTION

"Given an agent with certain functions and capabilities, in a world with certain functionally relevant opportunities and constraints, the agent's mental reactions (behavior, thought and feeling) will be only partially constrained by the situation it finds itself in. The freedom it has in which to act forces any action to reveal choice or bias in the agent, that may or may not be shown in other similar situations. **Personality** is the name we give to those reaction tendencies that are consistent over situations and time." *–Moffat, 1997 [1]*

We have developed a model of *Artificial Personality* (AP) that we have hosted on a custom built, social robot platform called Modroid. If we view personality as a strictly behavioral phenomenon, then all robots have some personality, that is a side effect of its programming. However, if we wish to systematically control behavior in a principled way, it is necessary to build an architecture with various "levers" that allow us to systematically tune or dial in a desired personality.

We purposefully choose a probabilistic representation of the cognitive state of the robot. We want the robot to generate behavior that seems appropriate to the situation, but is also unpredictable enough to make the personality of the robot interesting. The cognitive state includes emotions, motivation and perceptual cues.

While emotions, motivation and perception are represented explicitly as probabilities, personality is not explicitly represented. The personality of the robot is encoded in the Bayesian rules we use. The rules themselves are generated by separate program called the "Behavioral Generator."

The Behavioral Generator translates a description of the robot's personality into Bayesian rules in a principled way. The result is that our model is a discrete dynamical system model of personality rather than a symbolic model.

The Behavioral Generator was derived from a psychological test used to asses personality. This test is called the *International Personality Item Pool* (IPIP) evaluation [2]. Subjects answer a large number of questions, each related to some personality trait. At the most abstract level, there are five essential traits: **O**penness, **C**onscientiousnees, **E**xtroversion, **A**greeableness and **N**euroticism; easily remembered by the acronym OCEAN.

Interestingly, the questions used are related to the *behavior* of the individual. We can thus code these questions as actions for our robot. The correlation between a behavior and its trait is called its "loading factor", essentially a weight. We essentially invert this IPIP test to Generate Behavior. If we are given a description of a robot's personality, we can then compute the likelihood that the robot will choose a particular action. In future work, we imagine that a Robot IPIP— a personality test solely for robots– could be developed that is tuned to the capabilities of robots. For now, we use the Human IPIP to ensure the validity of our Behavioral Generator.

Notable previous work in Artificial Personality are by Petta and colleagues [3] and Moffat [1]. Petta stresses the importance of creating personalities for synthetic actors while Moffat discusses the various approaches that one can undertake to create artificial personality models. Read and colleagues [4] formulate a motive-based computational model of personality based on the structure and neurobiology of human personality. They simulated the creation of different personality characteristics in a gaming agent based on an underlying motivational agent. Their model is based on story structure and focused on two personality factors, Extroversion and Neuroticism.

In addition, there have been a number of efforts in creating computer personalities [5] [6] [7].

Table 1 Five Factors in a Nutshell

Personality Factor	Characteristics of Individuals High in Factor	Characteristics of Individuals Low in Factor
Personality Factor	Characteristics of Individuals High in Factor	Characteristics of Individuals Low in Factor
Openness	Creative Curious, Insightful, Intellectual	Bored, Intolerant, Routine-oriented, Uninterested
Conscientiousness	Dependable, Organized, Persevering, Punctual	Disorganized, Easily Discouraged, Reliable, Unpredictable
Extroversion	Active, Assertive, Excitable, Sociable	Apprehensive, Dull, Shy, Timid
Agreeableness	Amiable, Cooperative, Flexible, Trusting	Aloof, Contrary, Suspicious, Unfriendly
Neuroticism	Anxious, Depressed, Insecure, Susceptible to stress	Calm, Resistant to stress, Secure, Stable

2. ARTIFICIAL PERSONALITY MODEL

The inspiration for this work is a well formulated trait theory of personality called the "Five Factor Model" (FFM). Trait theories evaluates personality according to characteristics. The FFM is one formalization of trait theory [8]. The premise of FFM is that human personality traits can be described along five dimensions [9]:

- Openness (**O**) - **O** refers to the degree to which an individual is broad minded, curious and original. People who are open are generally curious and they have greater access to a variety of feelings, perspectives and ideas. However, closed individuals, those who have low **O**, are generally conservative and conventional.
- Conscientiousness (**C**) - Personality factor **C** refers to the tendency to show self-discipline, be organized and hard working. People who are high in the **C** factor plan carefully and are highly motivated in achieving their goals. In contrast, people with less **C** factor are generally aimless and unreliable. Their actions are usually spontaneous rather than well planned.
- Extroversion (**E**) - People with high **E** Factor are generally energetic, fun loving, highly sociable and full of positive emotions. They enjoy socializing and are stimulated in the company of others. However, people who are low in **E** Factor are reserved, independent and quiet.
- Agreeableness (**A**) - **A** refers to the tendency of being compassionate and cooperative. People who are high in **A** factor tend to be soft-hearted, good natured, helpful, forgiving, and altruistic. Those who have low **A** Factor can be rude, uncooperative, vengeful and suspicious.
- Neuroticism (N) - Factor **N** refers to the chronic level of emotional adjustment and instability. People with high **N** factor tend to experience unpleasant emotions very easily and they are prone to psychological distress. They have unrealistic ideas and have maladaptive coping responses.

These traits are usually measured as percentile scores [10], with the average mark at 50%. For example, a **C** rating in the 80th percentile indicates a greater than average sense of responsibility and orderliness.

The FFM structure does not imply that personality differences can be reduced to only five traits. Rather, these five dimensions represent personality at the broadest level of abstraction, and each dimension summarizes a large number of distinct, more specific personality characteristics. The FFM structure captures the commonalities among most of the existing psychological systems of personality description, and provides an integrative descriptive model for personality research. We felt that the FFM was the most clearly defined, and behavior oriented personality model and therefore the most amenable to computational implementation.

How would these personality traits affect the behavior of a robot? A robot that is more open would be more likely to explore its surroundings and would be attracted to novelty. A robot that is conscientious would be more likely to carry out a critical plan, e.g. assisting in surgery. An extroverted robot would make a good waiter at a restaurant. An agreeable robot would likely be good at cooperative game playing with humans, and might make a good personal entertainment robot. Finally, a neurotic robot might make a more interesting companion for some people than an even keeled robot.

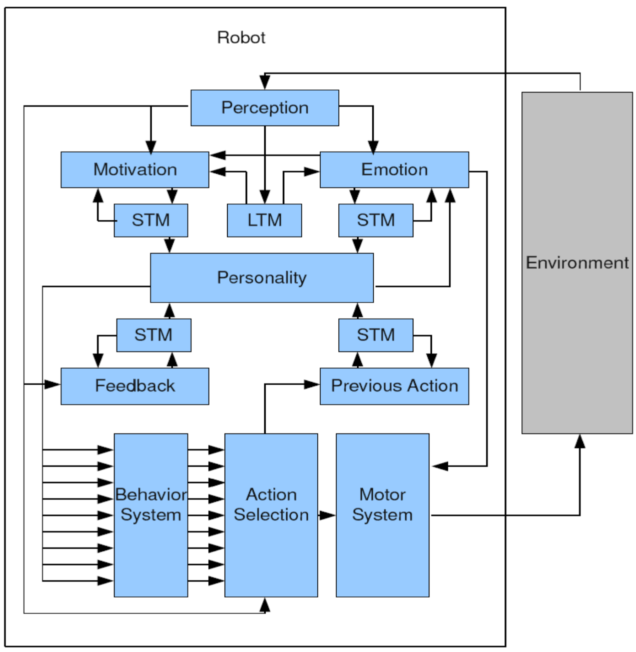
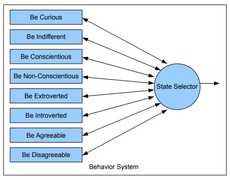


Fig. 1 Cognitive architecture incorporating personality, emotion and motivational system. See text for explanation.

3. RUNTIME COGNITIVE ARCHITECTURE OVERVIEW

In this section we describe the Cognitive Robot Architecture we developed to support experiments in AP. See Figure 1. The **Perception** module extracts perceptual cues from the surrounding environment and communicates to the motivation, emotion and action selection system. The **Behavioral Selection System** generates possible actions, **Action Selection** selects amount possible actions and the **Motor System** implements the selected action. The **Long Term Memory (LTM)** preserves the

(A) 

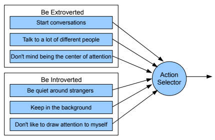
(B) 

Fig. 2 Behavior Selection System. (A) Complete set of behavioral state agents. (B) Actions comprising Be_Extroverted_S and Be_Introverted_S state agents.

robot's social interactions. LTM remembers conversations with people, which helps the robot recognize people and plays an important role in robot's social behavior. This memory can extend over the lifetime of a robot.

The **Personality Engine** is the heart of our AP architecture. The Personality Engine receives messages from **Short Term Memory** associated with four modules:

(i) **Emotion Module** - Emotions are holistic estimates of whether to expect positive or negative events in the near future.

(ii) **Motivation Module** - Volitional elements determines the goals of the robot. The motivation module is used to provide the robot with a purpose. Goals plus personality ultimately influence the robot's behavior.

(iii) **Feedback Module** - User feedback includes vocal, keyboard, and other messages delivered to the robot from people. Those messages are divided into three different types, which include negative, neutral, and positive.

(iv) **Previous Action Module** - In general, there should be some hysteresis in action selection. By biasing the agent to choose its previously selected action, the robot can be biased to be more stable or less stable. Previous Action keeps a record of the last selected action.

Erol and colleagues [11] showed similar use of both short-term and long-term memory in their architecture. We give more details in section 3.2 below.

3.1 Emotion, Motivation and Feedback

We consider five basic emotions **Happy**, **Sad**, **Angry**, **Scared**, and **Hope** from a pallete of possible emotions [12]. The emotion agent perceives symbolic input corresponding to stimuli from the external environment, or the internal STM. Based on the desirability of each input, the emotion agents generates a probability value for each emotion. This is similar to the model developed by [13] which are widely used in virtual character emotion modeling.

Likewise, the robot uses five basic motivations. These are: **Curiosity** , **Tranquility**, **Socialize**, **Satisfy Hunger**, and **Status** from a larger palette of possible motivations [14]. Each motivation agent uses symbolic inputs corresponding to external and internal stimuli and then generates a probability value for each motivational state.

Feedback receives messages from people and can be divided into three categories: **NEUTRAL**, **NEGATIVE**, and **POSITIVE**. This is a low bandwidth channel which operates over a relatively long time course.

Previous Action keeps track of recently performed actions. This can be used in our behavioral rules to increase the selection probability of recent actions.

3.2 Personality Engine

Using Bayes Theorem and an action selection table based on FFM, the **Personality Engine** computes the probability of choosing a behavioral goal. This probability is forwarded to the behavior agent system. The robot's actions are control by its **Behavioral Goals**. In principle, a robot might have dozens or even hundreds of Behavioral Goals. For the purpose of our experiments, we implemented eight Behavioral Goals, see Fig 2(A).

Each behavioral goal wraps up a collection of actions that can help the agent achieve the stated goals. For example, Fig. 2(B) shows an example of actions which can help achieve the Behavioral Goals of **Be_Extroverted** and **Be_Introverted**. For the goal of **Be_Introverted**, the robot uses the actions "Start conversations" , "Talk to a lot of different people", and "Don't mind being the center of attention" as ways of achieving its goal. As state above, the **Personality Engine** has the responsibility of selection the **Behavioral Goal** of the robot.

We can express the probability of the personality engine selecting an action as $P(Action_i^k|E_m, M_n, A_o^{K-1}, S_p)$,

where E is a vector representing the probability of being in a various emotional states, M is the probability of being in given motivational state, S is the feedback input, and $Action_i^k$ is the k-th action $Action_i$ taken by the robot, finally, k is a time index term, We consider a finite number of actions Q.

Note that $P(Action_i^k|E_m, M_n, A_o^{K-1}, S_p)$ is a true probability:

$$\sum_{i=1}^{i=N} P(Action_i) = 1 \tag{1}$$

$$0 \leq P(A = Action_i) \leq 1 \tag{2}$$

For compactness, let $\chi = [E, M, A_{k-1}, S]$ represent the cognitive state of the robot. Using the law of total probability, we can compute the probability of a particular action:

$$P(Action_i^k) = \sum_{c=1}^{C} P(Action_i^k|\chi) * P(\chi) \tag{3}$$

where $P(\chi)$ can be computed under the assumption that probability of each state does not have any inter relationship; that is, all are independent:

$$P(\chi) = \; = P(E_m) * P(M_n) * P(A_o^{K-1}) * P(S_p) \tag{4}$$

Personality traits function to select behaviors from among several different possibilities.

An essential part of our cognitive model is the idea of freedom of choice or free will. If a human commands the robot to execute a particular action, the robot may decide to obey or ignore. The likelihood of the robot carrying out a command will strongly depend on its personality, and its internal emotional state and its motivation. f the robot has a negative emotion associated with the individual giving the command, it may well decide to ignore the request or even do the opposite of the requested action. We give an overview of how this is accomplished below.

The computed action probabilities are then forwarded to behavioral selection. The probability is used to bias a cluster of actions, which we call *Action Categories*.

3.3 Behavior Selection System

The implemented behavior selection system includes nine different action categories, however, since the behavioral agent operates in parallel, it could support a very large number of action categories. Any particular Action Category becomes active when its activation probability passes a threshold. Only activated action categories are considered in the final action selection stage.

Each Action Category has sub-actions. The probability of selecting a sub-action is calculated with the aid of the sub-action selection table which is similar to that of action selection table. The action selection agent transfers the probability of each sub-action to the motor agent. Each motor agent sub-action has its own threshold level as well. If two or more sub-actions cannot be executed at the same time, the sub-action which has higher probability is executed first.

4. OFFLINE PERSONALITY GENERATOR

The Bayesian rules implicitly encode the personality of the robot. To set these rules, we use an off-line **Personality Generator**. We develop these rules by working from an standard personality evaluation tool used by psychologist, IPIP [2][15]. See the evaluation markers in Fig. 3. By crafting principled algorithms for generating Bayesian rules from makers, we ensure that the behavior generated accurately reflects the desired personality.

The left hand side of Eqn 3 is the probability of $Action_i^k$ given the state probability vector χ. $P(Action_i^k|\chi)$ encodes the personality of the robot. While the probabilities of emotion, motivation, previous action, and feedback agents are generated from each internal and external state occurrence, the value of these behavioral state selection probabilities under certain conditions can be decided arbitrarily. By determining $P(Action_i^k|\chi)$, we can control the personality. We can encode the personality as a large table of numbers. We call this table the **Behavioral State Selection Table**.

Since the total number of states is C, these conditional probability values can constitute a table dimension $C*Q$. Thus, Q different action agents exist.

4.1 Building State Selection Table

In this paper, eight different behavioral state agents are used. Be_Curious_S, Be_Extroverted_S and Be_Agreeable_S agents satisfies curiosity, socialize and status motivations respectively. While Be_Indifferent_S, Be_Introverted_S and Be_Disagreeable_S ignore each relevant motivations. Likewise, Be_Conscientious_S and Be_Non-Conscientious_S agents satisfies and dissatisfied hunger or tranquility motivations. When the Be_Conscientious agent is active, the robot is more likely to follow a plan and less likely to take a random action. Conversely, when Be_Non_Conscientious is active, the robot is more like to take a random action.

Probabilities of each behavioral state agent in a specific internal and external environment state are calculated by three principles:

- The behavior state activation probability is determined by five personality factor.
- Behavior state activation is driven by motivation.
- Emotion, Feedback and Previous Action biases the behavior state selection.

To implement these principles, a weight was assigned to each individual personality factor. The effect of the weight was to change the effect of each personality factors on the selection of an Action Category. All weights corresponded to published *loading factors*, essentially weights, given by Goldberg' work [16]. In that work, Goldberg determined how much each big five personality make effects on individual personality factor. From possible personality evaluation markers, 100 were selected.

Loading factors for actions inside an Action Category were averaged to create a loading factor for the Action Category (or behavioral state) as a whole. For example, we computed the Action category be_Extroverted to have weights [0.7, 0.1, 0.04, 0.1, 0.06] corresponding to E, A,C,N and O respectively. As expected, the loading factor for E is largest, that is, Extroversion will obviously have a significant effect on choosing a Be_Extroverted state. Agreeableness and Neuroticism will also have a significant effect on the Be_Extroverted state.

Motivation is an intrinsic need to accomplish a goal. Each goal can be satisfied by activation of a collection of behaviors. Thus each possible behavior is born from a specific motivation. The higher the motivation probability, the higher the associated behavioral state agent's Action Category. This emphasizes the selection of a relevant behavior state among all state agents under a specific motivation. For instance, when the Curiosity_M has the highest probability, Be_Curious and Be_Indifferent agents will get higher probability values than other categories. Likewise, when Socialize_M has higher activation level values than other motivations, probability values of Be_Extroverted and Be_Introverted will be highest among all action categories.

Emotion, like motivation, was an important factor affecting the dynamics of action selection. When sad, angry, or scared are core emotions at specific periods, different increments are assigned to the score of personality factors. For example, when the current emotion is sad, Be_Extroverted will have a minus increment while Be_Introverted will get a plus. Neuroticism is the tendency to experience emotional instability; if the robot has low level of emotional stability in its personality, it will

Label of Markers	Definition
E1	Am the life of the party
E2	Feel comfortable around people
E3	Start conversations
E4	Talk to a lot of different people at parties
E5	Don't mind being the center of attention
E6	Don't talk a lot.
E7	Keep in the background
E8	Have little to say
E9	Don't like to draw attention to myself
E10	Am quiet around strangers
C1	Am always prepared
C3	Get chores done right away
C5	Am exacting in my work
C6	Leave my belongings around
N2	Seldom feel blue
N3	Get stressed out easily
N10	Often feel blue

Fig. 3 List of Markers of FFM Evaluation in IPIP [2][17]

Fig. 4 Modroid with different emotions

tend to switch to sad or anger more easily. A low value of the emotional stability will increase the probability values of negative feelings.

Feedback and Previous Actions are the final factor that affect the action selection table. When humans receive positive feedback from other people after performing a specific action in a certain state, they tend to repeat the same action in the same state. To reflect this phenomenon, our architecture slightly increases the probability of selecting a previous action when positive feedback is sensed and decreases the probability when negative feedback is received. In case of previous action, there should be some hysteresis in action selection. By biasing the agent to choose its previously selected action, the robot can be biased to be more stable.

5. EXPERIMENTS

5.1 Robot Platform

To facilitate experiments, a social robot called "Modroid" was constructed by the RNSL lab at the University of Arizona, to carry out the experiments. Fig. 4 depicts the Modroid. The robot's dimensions are 45 x 40 x 23 cm. For computation, Modroid uses a Fit-PC 2, by Compulab. The Fit PC-2 using a Atom processor and uses less than 8 watts of power. The wheels and head movement are driven by Dynamixel AX-12 motors by Robotis. The shell was fabricated in ABS plastic using a 3-d printer. The vision software package OpenCV was used to implement Face detection. A headset and embedded speaker are used to facilitate communication with humans. Modroid expresses its feelings in two ways, using pre-recorded phrases and with a color LCD display. As shown in Fig. 4, two large color LCD displays are attached. The LCD make it possible for Modroid to express its emotion to people effectively. Modroid avoids obstacles with the aid of one IR sensor on the front of robot and two bump sensors on the side.

5.2 Experimental Setup

In this paper we demonstrate manipulation of one of the five factors: **Extroversion**. Throughout our experiments, Modroid had to interact with people and while navigating in an unknown area. In the experiments described here, Modroid was initialized with a happy emotion and began its navigation from small confined area. Modroid can escape from small confined area by using its IR sensor and bump sensors.

In first experiment, the personality of Modroid was chosen with maximum values of O, C, E, A, and a moderate value of N. In subsequent experiments, decreased values of O, C, E, A were used to observe the effects of these factors on the dynamics of action selection. Moreover, higher value of factor N was used to illustrate the effect of Neuroticism on emotional change and action selection.

5.3 Experimental Results

5.3.1 Motivation and Emotion

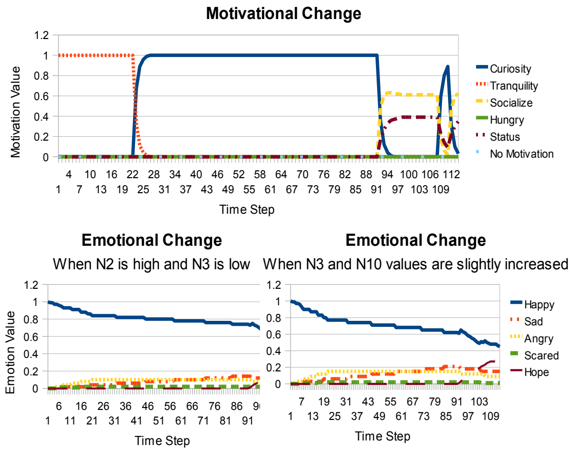


Fig. 5 Motivation and Emotion

Fig. 5 illustrates the changes in emotional and motivational probabilities a single run. The top graph of Fig. 5 illustrates motivational changes of Modroid in reaction to outside stimuli. From time 0 to time 21, Modroid was in confined area. This conflicts with the robot's motivation for **Tranquility** . Thus, from 0 to 22 time steps, the **Tranquility** motivation is at its maximum value. Modroid tries to satisfy **Tranquility** by trying to escape from the area during the period. At time 22, Modroid escaped from the area and started exploration of a wider area. As Modroid met a open area, **Curiosity** motivation increased and became the max value. This made Modroid navigate and travel around the area. At time 91, Modroid detected a stranger and **Curiosity** motivation is satisfied and decreases to a minimum. Modroid started a "conversation", an exchange of stock phrases, and talked with the person until time 107. After short exploration of area, Modroid meet a people again at time 111.

Bottom left graph shows emotional change when Modroid has high N2 and low N3. Refer to Fig 3 for definitions of N2 and N3. During confinement, the **Anger** emotion increased monotonically. As the robot navigated

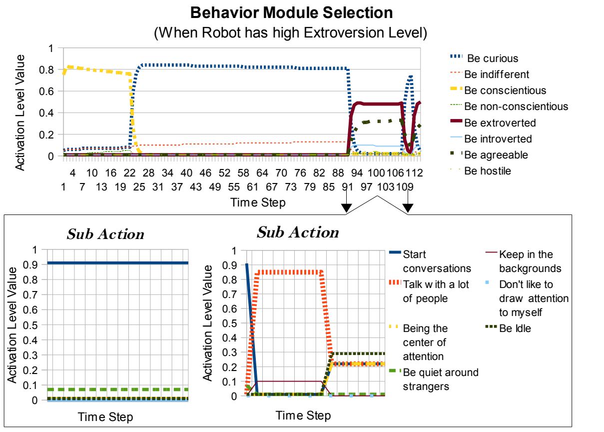


Fig. 6 Activation level change of behavioral state agents and actions, Behavioral state agents and sub actions at high Extroversion level

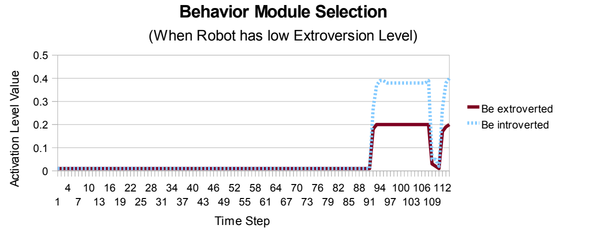


Fig. 7 Activation level change of behavioral state agents and actions, Behavioral state agents at low Extroversion level

in open area, the level of sad kept increasing while it reduce value of happy emotion. Then, when Modroid met a stranger, the value of hope increased rapidly.

To show effects from slight change of Neuroticism, bottom right graph show emotional change when N3 and N10 are increased slightly. Since high values in N3 and N10 markers means higher probability of being sad and angry, we can expect increased values of Sad and Angry emotion. By comparison with left graph, we can observe that the emotional values of sad and angry increased at a faster pace in this experiment due to change of Neuroticism factors. We also observed that the emotional values of sad and angry increased at a faster pace in the second experiment due to high Neuroticism level.

5.3.2 Action Agent

Top graph of Fig. 6 depict the probability eight different behavioral state agents when Modroid has high E, O, and C values. At time 0, Be_Conscientious was clearly highest among all possible behavioral states. This conscientiousness keeps the robot focused on escaping from its confinement. However, Be_Conscientious starts to decrease, almost as if the robot is becoming frustrated and is willing to switch actions. Further, the Angry emotion increases gradually as well. Although sub-actions are not depicted in this figure, Modroid repeated action between Be_prepared (for anything)(C1) and Do Planned Action(C5) which are actions under Be_Conscientious

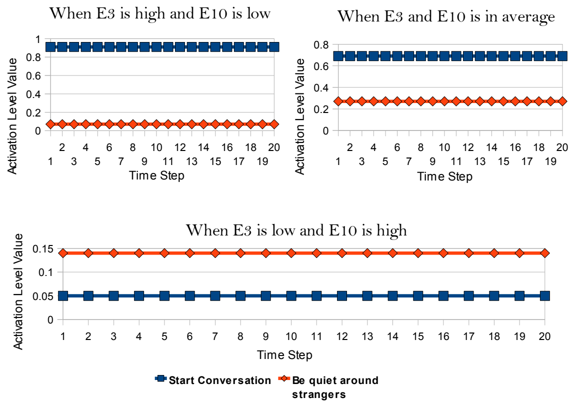


Fig. 8 Activation level of sub actions under three different sets of E3 and E10 factors.

state. In this experimentation, Be_prepared was used to detect obstacles and Do Planned Action was to avoid obstacles when they are detected. At time 22, Be_Curious became highest due to high O value when Modroid met entered and unknown area.

At time 91, when Modroid met a stranger, Be_Extroverted became higher than any other behavioral state agents owing to a high E level. During the conversation with the person, negative feelings like sad or angry decreased and Be_Extroverted maintained its probability value. The bottom graph of Fig. 6 shows probability values of subaction under Be_Extroverted agent in two different cases when Modroid have high E3 and E4. The bottom graphs give more detail of the time period when Modroid met a person. The left graph depicts the case when Modroid started the conversation with a person who met and continued the conversation with him alone. As can be seen in graph, Start Conversation action has the highest probability value while Be_Extroverted is activated. The right graph describes the case when other people participated in conversation between Modroid and a certain person. In this situation, Modroid talked with different people well rather than being in background of conversation, probably a result of a high E5 value.

Fig. 7 demonstrate probability values of Be_Extroverted and Be_Introverted when Modroid meet a person and has low Extroversion level. Compared with graph of Fig. 6, we can see that Be_Extroverted decreased and Be_Introverted increased by a large amount. This shows the effect of Extroversion factor on behavioral state agents. Although the levels of other behavioral states are not shown, other behavioral state experienced little change due to change of Extroversion level change. This is due to loading factor from Extroversion level on those behavioral state as described above.

Fig. 8 show activation level of sub actions under three different sets of E3 and E10 factors. The top left graph shows when the robot had high E3 and low E10, robot started a conversation when it met a stranger. On the other hand, the bottom graph shows that robot become be quiet in same situation if it has low E3 and high E10. The top

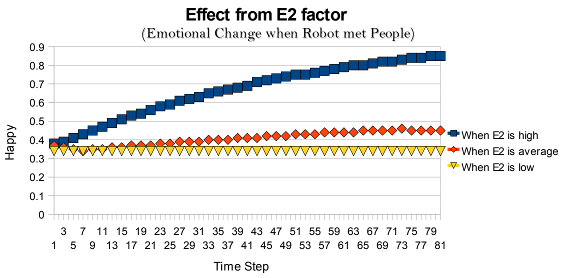


Fig. 9 Effect from E2 factor

right graph shows that robot started conversation when both E3 and E10 have an average value. This is because of effect from high Extroversion level. If our robot had a low Extroversion level, the robot might become quiet when it meet strangers though both E3 and E10 have an average value. Fig. 9 demonstrate effects of E2 factor on the level of the "happy" emotion. As value of E2 increased, the probability values of happy increased at a faster speed during conversation with people.

In consecutive experimentation, we set several different levels (low, mean, high) in factors in Extroversion and generated behavioral state and action graphs and emotion graphs. Like graphs in 6 and Fig. 8, the results was explicit and generated actions and emotional changes could be measured by 10 factors of Extroversion inversely.

6. CONCLUSION

In this article, we introduced a model of artificial personality implemented in a robot. This model has several unique features: i) It is probabilistic in nature i) It incorporates a personality generator, and iii) It contemplates all potential actions and select behaviors according to personality. In experiments, different personality factors showed different dynamics of action selection in a real environment, and the effects of emotion and motivation on action selection stage could be demonstrated.

We believe that our model provided us with an insight that artificial personality makes an important role in action selection and can be applied to future humanoid robots which can have various range of personalities. Future study will be focused on developing metrics to measure the personality of the robot.

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