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Autonomous Learning of Task Skills and Human Intention for Enhancing Human Trust of Robot Systems

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14. ABSTRACT

The PI's team proposed a framework in which a robot learns task skills enough to understand and execute a given task as reliably as possible. Motion significance and motion complexity measures that can be used to segment motion trajectories and assign MPWs (Motion Primitive Words) were implemented to accomplish this. The PI's team developed a method of regression of MPWs preserving motion significance to adapt, improve and/or reuse them. They also devised a method of representing pre- and post-conditions by analyzing motion significance of all possible object-object motion pairs and object-robot motion pairs. It was expected that a novel task skill can be acquired by compositionality of MPWs using working conditions represented by PDDL, and a robot can explain why the robot has to deploy a MPW under its current situation. This enhances human trust of robot systems. To show the validity of this framework, the team performed several experiments for learning task skills and social interaction skills for robots and digital avatars.

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"Autonomous Learning of Task Skills and Human Intention for Enhancing Human Trust of Robot Systems"

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Abstract: We propose a framework in which a robot learns task skills enough to understand and execute a given task as reliably as possible. To accomplish this, we suggest motion significance and motion complexity measures that can be used to segment motion trajectories and assign MPWs (Motion Primitive Words). Next, we develop a method of regression of MPWs preserving motion significance to adapt, improve and/or reuse them. We also devise a method of representing pre- and post-conditions by analyzing motion significance of all possible 'object-object' motion pairs and 'object-robot' motion pairs. We expect a novel task skill can be acquired by compositionality of MPWs using working conditions represented by PDDL. And, a robot can explain why the robot has to deploy a MPW under its current situation. This will enhance human trust to robot systems. To show the validities of this framework, we performed several experiments for learning task skills and social interaction skills for robots and digital avatars.

Introduction: Usually, in a common workspace, humans will trust a robot system if the system shows the reliable task-dependent motions that humans expect. To develop such a system, two aspects need to be considered as follows: (1) the system is able to execute necessary task skills dependably and (2) a skill has to be chosen immediately according to human intention and/or working conditions.

First, human trust can be increased if the robot is able to learn skill functionality enough to complete its task dependably from human experts. A task usually consists of a set of motion primitive words (MPWs). To understand such motion primitive words, let us consider an assembly example, "Insert a ring into a pole" task. In this example, a robot performs the task using a nominal sequence as follows: The robot first delivers a ring to a pole after picking it up. Next, it inserts the ring into the pole. Finally, the pole is delivered to the human. Here, "Approaching", "Picking", "Delivering", "Inserting", and "Releasing" can be considered as the MPWs for the "Assembly insertion" task.

The motion primitives and the sequence of motion primitives need to be modified or changed to resolve unexpected uncertainties and/or perturbations while the robot performs the task. Human trust in particular increases when the robot achieves its goals under such uncertainties and perturbations. For instance, i) if a robot can approach the objects by modifying the motion primitives of "Approaching" under different initial and goal configurations, ii) if the robot can re-grasp the objects by repeating the motion primitives of "Grasping" against the case that it fails to grasp the objects at its first trial, or iii) if the robot can grasp dropped objects by sequentially retrying MPWs "Approaching" or "Grasping" when it drops the objects, then the human will trust the robot.

Second, human trust can be also improved if a robot selects a skill in accordance with human intention with any delays. In particular, a robot needs to understand human intention while interacting with a human for a co-operative task execution. The robot needs to learn signals that lead human intention which triggers for the robot to change MPW. Here, there will be learned relationships between MPWs and human intention. The robot then chooses skills in accordance with the recognized human intention. For instance, suppose that a human wants to get a plain pole without ring. And suppose that at this instant, the robot is approaching a ring to pick up. If the robot detects a signal leading such human intention, then the robot immediately stops approaching, and pick up a plain pole without ring. In this case, the human trust will grow.

During three years of period of performance, we worked on following four WorkStreams (WSs) to enable robots to learn and reuse motion primitives words(MPWs) replicating how humans learn and reuse MPWs as if humans can make composition of verbal words to generate a variety of sentences in linguistics:

- WS #1: Segmentation of motion trajectories: Dividing motion trajectories into meaningful segments [1, 3, 6]
- WS #2: Representation of motion primitives: Representing each motion segments as a word (MPW) [2, 7]
- WS #3: Learning motion grammar: Performing a series of significance analysis by calculating associations between MPWs and surrounding objects in order to the target object [2, 3]
- WS #4: Reorganization of MPWs to execute new tasks: Executing given tasks by leveraging (reuse, modify and/or adapt as necessary) listed procedures. [6, 7]

Experiment: Before developing the four WSs, we first defined motion significance and motion complexity measures: Motion significance is obtained by dividing temporal entropies by spatial entropies calculated from Gaussian mixtures. Motion complexity is computed by the averaged amount of motion significance in a set of demonstrations [3].

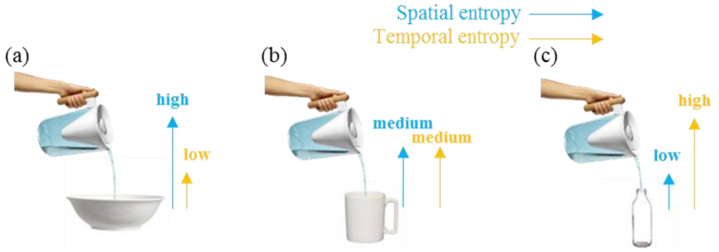

Fig. 1 The pouring task: (a) Quick pouring water into a bowl, which has a large-size mouth, (b) Normally pouring water into a cup, which has a medium-size mouth, and (c) Slow and cautious pouring water into a bottle, which has a small-size mouth.

As shown in Fig. 1, fine-grained motions (see Fig. 1(c)) will show both small spatial entropies and large temporal entropies when compared with coarse-grained motions (see Figs. 1(a) and 1(b)). On the other hand, coarse-grained motions will show both large entropies and small temporal entropies when compared with fine-grained motions. Here, our motion significance and motion complexity measures are designed to attain large values, if the demonstrated motion is fine-grained as shown in Fig. 1(c) in comparison with coarse-grained ones [2, 7].

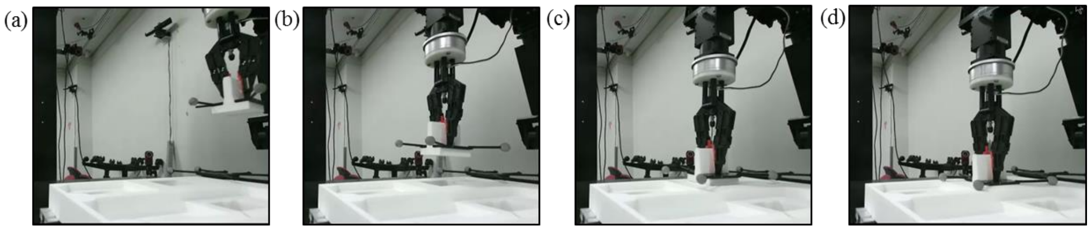

Fig. 2 Illustrations of motion primitives in the peg-in-hole task: (a) Approaching, (b) Falling, (c) Rubbing, and (d) Inserting, respectively.

(WS #1) We proposed an autonomous segmentation technique in which segmentation points are obtained from Gaussian mixtures [1, 3]. Here, such Gaussian mixtures were learned and improved by considering motion significance and motion complexity. We evaluated our segmentation technique using TUM kitchen dataset and observed over 90% similarity compared to manual segmentation by an expert. And, we verified and extended motion significance and motion complexity measures to force/torque trajectories, as shown in Fig. 2 [3, 6].

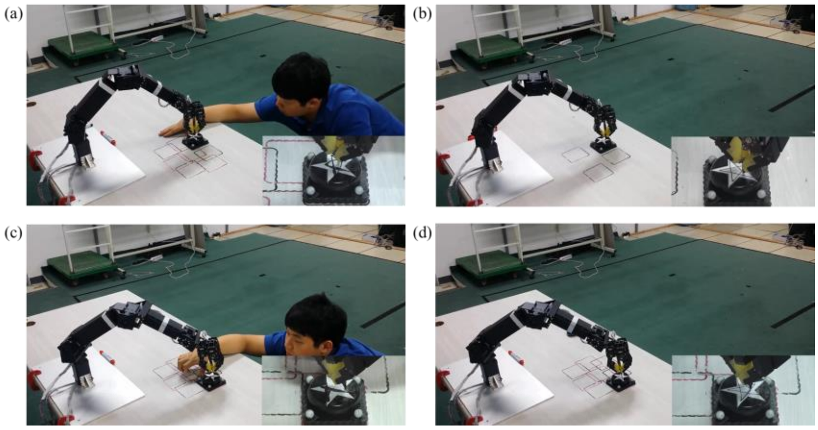

Fig. 3 Results of motion regression in known and unknown locations while executing 'Cookie Decoration' task: the results of (a) conventional approach in known location, (b) our proposed approach in known location, (c) conventional approach in unknown location, and (d) our proposed approach in unknown location, respectively.

(WS #2) Next, we developed an optimization technique for motion regression by which a robot was able to adapt learned motion primitives in unknown locations, as shown in Fig. 3 [2, 7]. We also devised a method to generalize motion primitives in such a way that motion significances are preserved when adapting and reusing those ones. A variety of Gaussian mixtures can be generated by using linear transform of the means (of Gaussian mixtures) and by adjusting eigenvalues and eigenvectors of the covariance (of Gaussian mixtures).

(WS #3) MPWs are then associated with significant variables by analyzing motion significance. And, we determined which object the robot should pay attention to during motion trajectories to activate motion primitives by analyzing motion significances of all possible 'object-object' motion pairs and 'object-robot' motion pairs. As a result, we found pre- and post-conditions for a task execution. Here, pre-condition and post-condition denote what has to be checked to activate motion primitives and what has been changed after executing the motion primitives, respectively [2, 3].

(WS #4) To make composition of our MPWs, we developed task planning system in which a new task can be planned by using motion primitive words (MPWs) and their pre- and post-working conditions learned and collected from several different tasks. For this, we extracted semantic motion rules represented by PDDL [6, 7].

Results and Discussion (I) [3]: We proposed two novel measures to specify motion significance and motion complexity from human motion trajectories. We showed that motion significance can be measured by considering both temporal entropy and spatial entropy of a motion frame, based on the analysis of Gaussian mixtures learned from human motions. Motion complexity is then calculated by measuring the averaged amount of motion significance involved in all time indexes of motion trajectories. These two measures are devised to satisfy the requirement of neural complexity measure proposed to attain small values for totally random or totally regular activities.

To show that the proposed measures are consistent with our intuitive notion of motion significance and motion complexity, several human motions for drawing and pouring are analyzed by means of motion significance and motion complexity. Furthermore, our complexity measure is compared with three existing measures to analyze their similarity and dissimilarity.

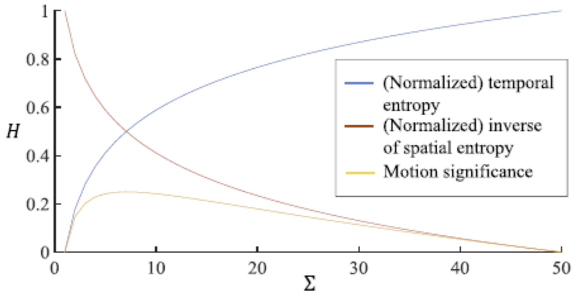

Fig. 4 Temporal entropy, inverse of spatial entropy, and motion significance according to temporal and spatial variations. Here, the blue and red lines indicates temporal entropy and inverted spatial entropy according to spatial variation and temporal variation, respectively. The yellow line indicates motion significance calculated by dividing temporal entropy by spatial entropy. Here, motion significance shows a bell-like shape according to temporal and spatial variations.

To be more specific, motion significance is measured by dividing temporal entropy by spatial entropy to satisfy the requirement of neural complexity. Surprisingly, motion significance shows a bell-like shaped relation according to temporal variations and spatial variations as neural complexity, as shown in Fig. 4 [3]. Therefore, motion significance can be used to measure relative meaningfulness of each motion frame because the requirement of a neural complexity measure is satisfied. In a different viewpoint, it was possible to measure the significance of motion at every time index of human motions by considering precision (from the perspective of spatial variation) and carefulness (from the perspective of temporal variation). In addition, motion complexity is directly proportional to motion significance because motion complexity is averaged motion significance. Thus, motion complexity can be used to measure the number of meaningful motions contained in a set of human motions.

To evaluate our two measures, various analyses are performed using human tasks of two types: drawing and pouring. The drawing and pouring tasks are first executed by humans of two types as follows: (i) an expert who can perform very fast and very accurate executions without any failures and (ii) a beginner who has lower capability compared with the expert in (i). The beginner must execute the two tasks with deliberation to accomplish them. In general, humans tend to precisely (in the viewpoint of spatial entropy) and carefully (in the viewpoint of temporal entropy) execute motions if their tasks are difficult and complex. Therefore, motion complexities can be different according to capabilities of humans, even in a single task. Our complexity measure of an expert is smaller than that of a beginner. In fact, the expert can easily and quickly execute the tasks. However, a beginner should precisely and carefully execute motions such that these motions are dissimilar and difficult to avoid failures. As a result, skillfulness of humans is an important role to determine motion significance and motion complexity in a task.

On the other hand, the LMC complexity measure is difficult to identify its complexity values between an expert and a beginner. Even though the LMC complexity measure seems to have the similar performance with our complexity measure, it is dissimilar with not considering temporal information of human activities.

Fig. 5 Three figures drawn by the beginner; (a) figure with random patterns, (b) figure with a mixture of random and star-shaped patterns, and (c) figure with straight lines.

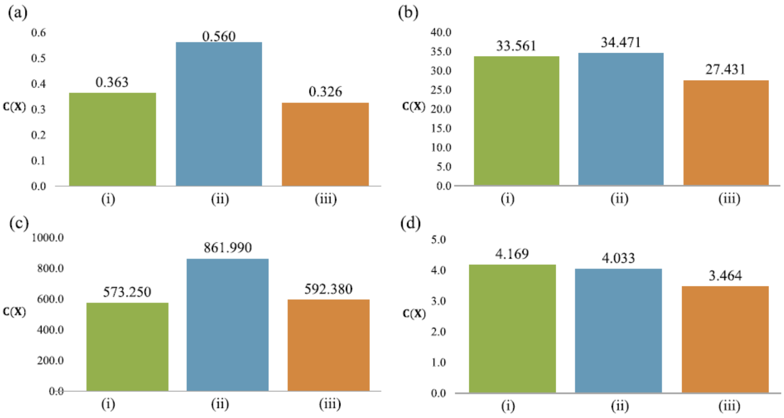

Fig. 6 Complexity values obtained from human motions generated to achieve three tasks of Fig. 5(a)-(c): (a) when applying our proposed complexity measure, (b) when applying the neural complexity measure, (c) when applying the LMC complexity measure, and (d) when applying the complexity measure based on permutation entropy, respectively. In these all figures, (i), (ii), and (iii) indicate the complexity values from Fig. 5(a)-(c), respectively.

To carry out various evaluations, we then calculate motion complexities in Fig. 5(a)–(c) such as in Fig. 6. The motion complexities of Fig. 5(b) obtained from our complexity measure, as shown in Fig. 6(a), are higher than those in Fig. 5(a) and 5(c), which satisfies our objectives. Fig. 6(b)–(d) show the complexity values obtained by the neural complexity, the LMC complexity, and the complexity based on permutation entropy, respectively. These complexity values obtained from our complexity measure (see (i)–(iii) of Fig. 6(a)) and the LMC complexity measure (see (i)–(iii) of Fig. 6(c)) except for the complexity measure based on permutation entropy (see (i)–(iii) of Fig. 6(d)) are similar with the neural complexity measure see (i)–(iii) of Fig. 6(b)) by satisfying the requirement of attaining small values in totally random or totally regular motions. On the other hand, the motion complexity values obtained from the complexity based on permutation entropy in the figure with random pattern are higher than those in the figures with regular patterns. As a result, the complexity measure based on permutation entropy did not satisfy the requirement of neural complexity because of being higher when increasing randomness of human motions.

Results and Discussion (II) [5]: We used the motion significance to model social interaction by selecting the information that plays key roles in recognizing the interaction between a human and a virtual humanoid robot. Following the learning-from-demonstrations (LfD) paradigm, we aimed to enable believable human-robot interaction by first recognizing the social interactions between two human performers, and then by reproducing them using a cognitive virtual humanoid robot. We achieved such goal by devising a motion significance metric which tends to be higher in slow and precise relative motions. Usually, such motions are useful for recognizing social interactions. To calculate motion significance, we first obtained the relative information between all possible pairs of joint positions, each of which is extracted from a pair of joints of two human interactions. Then, the temporal entropy and the spatial entropy are measured based on Gaussian mixture models, and the motion significance is measured by combining temporal entropy and spatial entropy. Finally, we extracted significant information (i.e., significant variables) of social interaction based on the measured motion significance values. To evaluate the proposed method, we built hidden Markov models (HMMs) using the information selected based on motion significance, and experimentally show that our method significantly improves the recognition performance of existing HMM methods in two social interaction scenarios: high-five and handshaking.

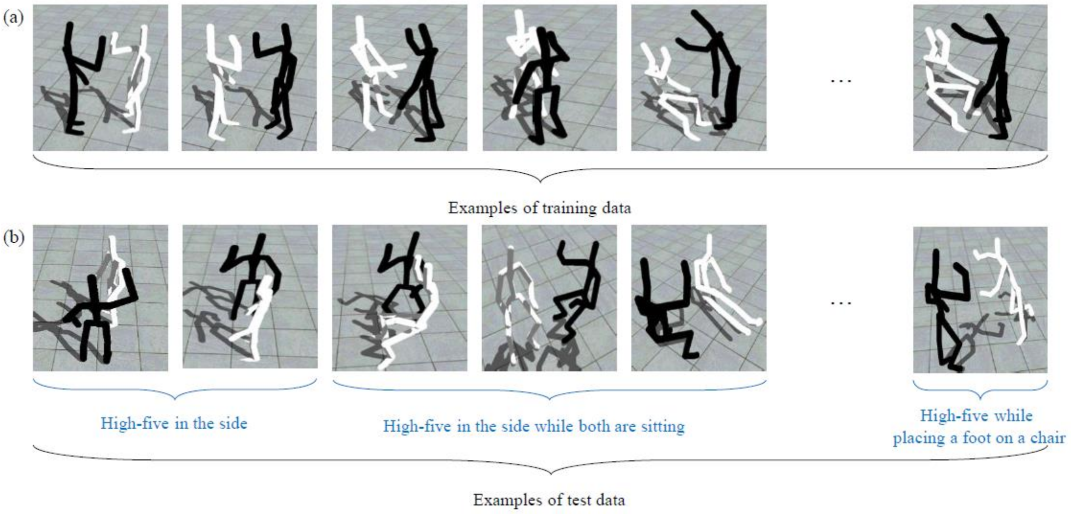

Fig. 7 Examples of training data sets and test data sets for high-five social interactions: (a) A training data set, (b) A test data set. The test data includes various interaction postures which are not in the training data. For examples, two humans sit on the side or sit on a chair to get a total of 16 data of high-five interaction.

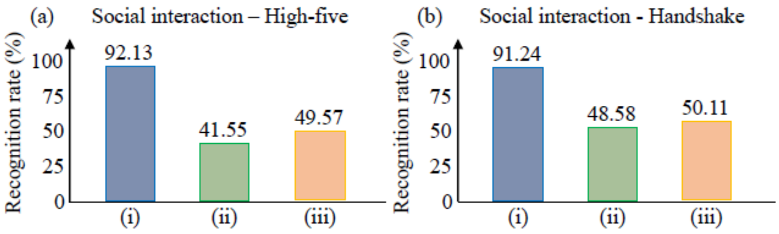

Fig. 8 Recognition rates of HMMs modeled by selecting significant information using motion significance, information gain, and PCA: (a) Recognition rates for high-five interaction - (i) 92.13%, (ii) 41.55%, and (iii) 49.57% and (b) Recognition rates for handshake - (i) 91.24%, (ii) 48.58%, and (iii) 50.11%. Here, (i), (ii), and (iii) are the results by proposed method, by information gain, and by PCA, respectively.

The test data of the HMMs model is shown in Fig. 8. As shown in the figure, we performed verification of high-fives and handshakes of very different positions and attitudes for the two human positions and attitudes from those used in the learning. Representative methods for selecting information include feature selection and feature extraction methods. Our method can be seen as one of the possible ways to select features. In order to compare our method with these, we compared our method with the method of using information gain, which is one of representative methods in feature selection, and the method of using PCA, which is also one of representative methods, as shown in Fig. 8(a). As shown in the Fig. 8(a), the information gain of the relative information is calculated, and ten pieces of information are selected based on the information gain. Then, HMMs are modeled using this information. For all those feature extraction methods, we modeled HMMs with ten features. We compared three different sets of HMMs, using the information gain, using ten eigenvectors from PCA, and using variables selected by the proposed method, respectively. As shown in Fig. 8(b), the HMMs performances of the proposed method for high-five and shaking hands are 92.13%, 91.24%, and the performances of the HMMs modeled by the information gain are 41.55%, 48.58% and the performances of the HMMs modeled by PCA are 49.57% and 50.11%, respectively. In the case of information gain, it is a method to extract information with low mutual dependency. This does not guarantee that the selected information plays a significant role in the interaction, and it does not guarantee that it contains significant information for interaction recognition, since it is an indicator of how independent the information is.

In the case of PCA, it is possible to reduce the dimension of the training data by projecting the dimension to the axis where the dispersion of the data is large, so that it is possible to reduce the dimension of the learning data, but it is not guaranteed that the reduced space can represent important information for recognizing the social interaction. As shown in this experiment, the proposed method is a more appropriate method for finding significant information for recognizing social interaction.

[References]

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[4] S. H. Lee, M. G. Kim, and I. H. Suh, "Enhancement of Layered Hidden Markov Model by Brain-inspired Feedback Mechanism," 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2014.

[5] Nam Jun Cho, Sang Hyoung Lee, Taesoo Kwon, and Il Hong Suh, "Probabilistic Representation of Social Interaction based Motion Significance," in preparation.

[6] N. J. Cho, I. H. Suh, S. H. Lee, "Self-Programming robot tasks by Motion Significance and PDDL," in preparation

[7] N. J. Cho, S. H. Lee, I. H. Suh, H. S. Kim, "Autonomous Learning How to Interact in a Human-Robot Join Assembly Work," 2016 13th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), 2016

List of Publications and Significant Collaborations that resulted from your AOARD supported project:

a) papers published in peer-reviewed journals,

- I. H. Suh, S. H. Lee, N. J. Cho, and W. Y. Kwon, "Measuring Motion Significance and Motion Complexity," Information Sciences, vol.388-389, pp.84-98, 2017.

b) papers published in peer-reviewed conference proceedings,

- S. H. Lee, M. G. Kim, and I. H. Suh, "Enhancement of Layered Hidden Markov Model by Brain-inspired Feedback Mechanism," 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2014.
- N. J. Cho, S. H. Lee, I. H. Suh, H. S. Kim, "Autonomous Learning How to Interact in a Human-Robot Join Assembly Work," 2016 13th International Conference on Ubiquitous Robots and Ambient Intelligence (URAl), 2016

c) papers published in non-peer-reviewed journals and conference proceedings,

- None

d) conference presentations without papers,

- I. H. Suh, ICT Workshop: Trust in Autonomy, USC Institute for Creative Technologies, USA, August 19-21, 2015.
- I. H. Suh, "Autonomous Learning of Task Skills and Human Intention for Enhancing Human Trust of Robot Systems," 2016 Trust and Influence Program Review, Arlington, VA, USA, June 13-17, 2016.
- I. H. Suh, "Action-driven Incremental Graph Structuring for Object Representation and Recognition," IEEE Ro-Man 2015, Kobe, Japan, August 31-September 4, 2015.

e) manuscripts submitted but not yet published, and

- N. J. Cho, I. H. Suh, S. H. Lee, "Self-Programming robot tasks by Motion Significance and PDDL," in preparation
- Nam Jun Cho, Sang Hyoung Lee, Taesoo Kwon, and Il Hong Suh, "Probabilistic Representation of Social Interaction based Motion Significance," in preparation.

f) provide a list any interactions with industry or with Air Force Research Laboratory scientists or significant collaborations that resulted from this work.

- Prof. Bernhard Hengst, "Towards Autonomous Adaptation and Trust," CSE, University of New Wales, November 6, 2015.
- Dr. Jeremy Knopp and Dr. Misoon Mah, Project Meeting, December 14, 2016.

Attachments: Publications a), b) and c) listed above if possible.

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