Toward Automated Generation of Affective Gestures from Text: 
A Theory-Driven Approach

Micol Spitale  
micol.spitale@polimi.it  
PhD at Politecnico di Milano  
Milan, Italy  
Visiting PhD at the University of Southern California  
Los Angeles, California, USA

Maja J Matarić  
mataric@usc.edu  
University of Southern California  
Los Angeles, California, USA

ABSTRACT
Communication in both human-human and human-robot interaction (HRI) contexts consists of verbal (speech-based) and non-verbal (facial expressions, eye gaze, gesture, body pose, etc.) components. The verbal component contains semantic and affective information; accordingly, HRI work on the gesture component so far has focused on rule-based (mapping words to gestures) and data-driven (deep-learning) approaches to generating speech-paired gestures based on either semantics or the affective state. Consequently, most gesture systems are confined to producing either semantically-linked or affect-based gestures. This paper introduces an approach for enabling human-robot communication based on a theory-driven approach to generate speech-paired robot gestures using both semantic and affective information. Our model takes as input text and sentiment analysis, and generates robot gestures in terms of their shape, intensity, and speed.

CCS CONCEPTS
• Human-centered computing → HCI theory, concepts and models; • Computing methodologies → Modeling methodologies.

KEYWORDS
affective gestures, robot, text-to-gesture, cognitive linguistics, multimodal interaction

ACM Reference Format:
Micol Spitale and Maja J Matarić. 2018. Toward Automated Generation of Affective Gestures from Text: A Theory-Driven Approach. In Woodstock ’18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY. ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION AND BACKGROUND
Humans convey information through both verbal and nonverbal channels. About 70% of human communication is nonverbal [20], and involves body language (i.e., body posture, facial expressions) and features of speech (i.e., intonation, prosody). The communicated content contains both semantics (meaning) and affect content.

In HRI, research has explored both verbal communication [2, 13, 30] leveraging advances in Natural Language Processing (NLP) [31], and nonverbal communication (e.g., prosody [17, 28, 29], robot gesture [3, 35], facial expressions [7, 8], and gaze [1, 23]). Work HCI, simulated agents, and virtual humans has also explored simulated nonverbal communication features [24, 27].

Synchronizing speech and gesture is an important component of natural and effective robot communication in HRI. Work on automated gesture generation to date has focused on rule-based approaches (i.e., creating dictionaries for mapping words to gestures [11]) and data-driven approaches (i.e., exploiting deep-learning [14, 36]), producing speech-paired gestures on either semantics or affective state, respectively. A few exceptions, including Lhomme and Marsella [15] and Ravenet et al. [25], designed rule-based models to produce both semantically-linked and affective-based gestures, but that work was only done for virtual agents and not robots. Rule-based approaches are limited to fixed a priori mappings, while data-driven approaches lack interpretability.

This work introduces the design of a theory-driven approach for automatically generating speech-paired robot gestures based on both semantic and affective information. Our design is grounded in the theories of Image Schema [9, 12, 26] and Embodied Cognition [34], Johnson [12] defined an image schema as “a recurring dynamic pattern of our perceptual interactions and motor programs that gives coherence and structure to our experience”. Wilson [34] defined embodied cognition on the theory that “cognitive processes are rooted in the body’s interactions with the world”. Additionally, our approach is informed by McNeill [18]’s classification of gestures as iconic (i.e., resembling a physical aspect of conveyed information), metaphoric (i.e., iconic gestures that refer to abstract concepts instead of concrete entities), deictic (i.e., pointing to an object, person, or directions), and beat (i.e., dictated by the rhythm of speech).

Our theory-driven approach is designed for HRI and consists of a sequence of modules with a single goal. The model receives text as input, analyzes its semantic and affective dimensions, and then generates speech-synchronized gestures that communicate both meaning and emotion.

This work aims to make the following contributions:
(1) The first use of a combination of theories of Image Schema and Embodied Cognition;
(2) The ability to automatically generate gestures that communicate both semantic and affective components of speech;
The ability to use machine learning as part of the gesture generation in an interpretable way.

## 2 FROM THEORIES TO A COMPUTATIONAL MODEL

From the psychology literature, the embodied cognition theory refers to the idea that "states of the body modify states of the mind" [33]. As part of our reasoning, we interact with the world through embodiment via language structures (acoustical and optical) which results in the mental representations we exploited to inform our abstract and concrete concepts. Johnson [12] suggested that as humans we use similar patterns of reasoning, called Image Schemas. Image Schema enables us to map common concepts to different concrete and abstract entities. It enhances our perception and explains how we interact and move in a specific environment, grounding the language structure and meaning. Within the cognitive linguistic literature on embodied cognition, Cienki [5] suggested that the language structure and meaning is based on the embodied experience, and that they are naturally aligned with the production of gestures during speech. Many authors showed promising results about the use of Image Schema as mapping between conceptual entity and the language production for both speech and gestures [4, 16].

Mittelberg [21] described the gesture of mimicking the shape of a box, and the authors explained how this gesture can represent the Image Schema OBJECT or CONTAINER. The CONTAINER recalls the idea of having an entity within boundaries which elements can be inside or outside it. Each Image Schema leads to a different representation in the real world characterized by different body position and movements.

We took inspiration from these works to design our new model which is grounded on Embodied Cognition and Image schema theories, and which sought to bridge the acoustic (i.e., speech) and optical (i.e., gesture) language structures to inform robotic platforms.

## 3 MODEL ARCHITECTURE

Our theory-based approach involved a sequence of modules that generate a gesture synchronized with speech from a text input, as follows:

1. **Text analysis.** Speech Mapper, Affect Mapper, and Image Schema Mapper modules run in parallel and analyze the timing, sentiment, and semantics of the text, respectively. Speech Mapper returns the timing and duration of all the words in the text, the Affect Mapper maps the words to an affective meaning that corresponds to the valence, arousal, and dominance values obtained from affective lexicon analysis [22]. In case the input text has no words that correspond to any affective value, we compute the sentiment of the whole sentence [19]. Next, the Image Schema Mapper returns the corresponding Image Schema of the words that represent an iconic meaning in the input text.

2. **Word filtering and mapping.** The Word Filter analyzes the input text and tags part of speech exploiting an NLU library [10]. In addition, it discards words that do not provide any semantic value (e.g., prepositions, articles). The Word Mapper returns only words with a corresponding Image Schema mappings and emotional states, as well as speech-timing information. If a word associated with an Image Schema does not correspond to any affective state, it is associated with the sentiment of the whole sentence.

3. **Extrapolating gesture shape and parameters.** The Gesture Parameter Extractor takes the affective state of each word and it returns the associated gesture speech, timing and amplitude according to valence and arousal value of the corresponding word [32]. The Gesture Shape Extractor takes as input the Image Schema corresponding to the word and it returns the shape of the gesture.

4. **Gesture selection.** The Gesture Ranker makes decisions on what gesture to perform. This module ranks gestures based on their affective state and meaning in the context of the sentence. The results from the previous steps could be two or
more gestures associated to specific words with iconic meaning. To ensure that it is acting naturally and believably, we rank the gestures in the sentence so that the robot performs a single gesture per sentence.

(5) Gesture synthesis. The model synthesizes the text into speech (Text-to-Speech), and generates the gesture (Gesture Generator) selected in previous steps (e.g., motion of robot joints according to the input text, synchronized with speech) exploiting the MoveIt framework [6], also making it ROS-compatible.

Our ongoing work on the model involves an empirical study that evaluates the model’s effectiveness and interpretability.

4 CONCLUSION AND FUTURE WORK

This work introduced an approach for automatically generating robot gestures from speech with both semantic and affective meaning. To the best of our knowledge, this is the first gesture generator grounded in cognitive linguistic theories and communicates both semantic and affective information. The interpretable approach uses a sequence of single-purpose modules that exploit both data-driven and rule-based methods. In ongoing work, we are evaluating the approach empirically to assess its efficacy and interpretability.

ACKNOWLEDGMENTS

This research was supported in part by the University of Southern California (supporting Maja Mataric), and in part by EIT Digital (supporting Micol Spitalie). The authors thank Gianna Beck and Sarah Okamoto for their help with the implementation process.

REFERENCES

[1] Henny Admoni and Brian Scassellati. 2017. Social eye gaze in human–robot interaction: a review. Journal of Human-Robot Interaction 6, 1 (2017), 25–63.
[2] Yonatan Biuk, Deniz Yuret, and Daniel Marcu. 2016. Natural language communication with robots. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 751–754.
[3] Paul Brenner, Anthony Pipe, Chris Melluish, Mike Fraser, and Sriram Subramanian. 2009. Conversational gestures in human-robot interaction. In 2009 IEEE international conference on systems, man and cybernetics. IEEE, 1645–1649.
[4] Kawai Chui. 2011. Conceptual metaphors in gesture. Cognitive Linguistics 22, 3 (2011).
[5] Alan Cienki. 2013. Image schemas and mimetic schemas in cognitive linguistics and gesture studies. Review of Cognitive Linguistics. Published Under The Auspices of the Spanish Cognitive Linguistics Association 11, 2 (2013), 417–432.
[6] David Coleman, IoanSucan, Sachin Chitta, and Nikolaus Correll. 2014. Reducing the barrier to entry of complex robotic software: a MoveIt case study. arXiv preprint arXiv:1404.3795 (2014).
[7] Jia Deng, Gaoyang Pang, Zhiyu Zhang, Zhiho Pang, Huayong Yang, and Geng Yang. 2019. cGAN based facial expression recognition for human-robot interaction. IEEE Access 7 (2019), 9848–9859.
[8] Shuzhi Sam Ge, Chen Wang, and Chang Chieh Hang. 2008. Facial expression imitation in human robot interaction. In RO-MAN-2008-The 17th IEEE International Symposium on Robot and Human Interactive Communication. IEEE, 213–218.
[9] LAKOFF, George. 1987. Women, fire, and dangerous things: What categories reveal about the mind. Chicago: University of Chicago Press.
[10] Nitin Harderai, Jacob Perkins, Deepthi Chopra, Nisheeth Joshi, and Itt Mithur. 2016. Natural language processing: python and NLTK. Packt Publishing Ltd.
[11] Chien-Ming Huang and Bilge Mutlu. 2013. Modeling and Evaluating Narrative Gestures for Humanlike Robots. In Robotics: Science and Systems. 57–64.
[12] Mark Johnson. 1987. The Body in the Mind: The Bodily Basis of Meaning, Imagination. Reason (1987).
[13] James Kennedy, Séverin Lemaignan, Caroline Montassier, Pauline Lavalade, Bahar Irfan, Fotios Papadopoulos, Emmanuel Senffe, and Tony Belpaeme. 2017. Child speech recognition in human-robot interaction: evaluations and recommendations. In Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction. 82–90.
[14] Taras Kucherenko, Patrik Jonell, Sanne van Waveren, Gustav Eje Henter, Simon Alexanderson, Iolanda Leite, and Hedvig Kjellström. 2020. Gestimulator: A framework for semantically-aware speech-driven gesture generation. arXiv preprint arXiv:2001.09326 (2020).
[15] Margaux Lhomme and Stacy C. Marsella. 2013. Gesture with meaning. In International Workshop on Intelligent Virtual Agents. Springer, 303–312.
[16] Andy Lücking, Alexander Mehler, Désirée Walther, Marcel Mauri, and Dennis Kurfürst. 2016. Finding recurrent features of image schema gestures: the figure corpus. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16). 1426–1431.
[17] Erik Marchi, Fabien Ringeval, and Björn Schuller. 2014. Voice-enabled assistive robots for handling autism spectrum conditions: an examination of the role of prosody. In Speech and Automata in Health Care. De Gruyter.
[18] David McNeill. 1992. Hand and mind: What gestures reveal about thought. University of Chicago press.
[19] Fafa Medhat, Ahmed Hassan, and Hoda Korashy. 2014. Sentiment analysis algorithms and applications: A survey. Ain Shams engineering journal 5, 4 (2014), 1093–1113.
[20] Albert Mehrabian. 2017. Nonverbal communication. Routledge.
[21] Irene Møllberg. 2018. Gestures as image schemas and force gestalts: A dynamic systems approach augmented with motion-capture data analyses. Cognitive Semantics 11, 1 (2018).
[22] Sad M. Mohammad. 2018. Obtaining Reliable Human Ratings of Valence, Arousal, and Dominance for 20,000 English Words. In Proceedings of The Annual Conference of the Association for Computational Linguistics (ACL). Melbourne, Australia.
[23] Ajung Moon, Daniel N Troniak, Brian Gleeson, Matthew KJX Pan, Minhua Zheng, Benjamin A Blumer, Karen MacLean, and Elizabeth A Croft. 2014. Meet me where i’m gazing: how shared attention gaze affects human-robot handover timing. In Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction. 334–341.
[24] Nahal Norouzi, Kangsoo Kim, Jason Hochreiter, Myungho Lee, Salam Daher, Gerd Bruder, and Greg Welch. 2018. A systematic survey of 15 years of user studies published in the intelligent virtual agents conference. In Proceedings of the 18th international conference on intelligent virtual agents. 17–22.
[25] Brian Ravenet, Catherine Pelachaud, Chloé Clavel, and Stacy Marsella. 2018. Automating the production of communicative gestures in embodied characters. Frontiers in psychology 9 (2018), 1144.
[26] Tim Rohrer. 2005. Image schemata in the brain. From perception to meaning: Image schemas in cognitive linguistics 29 (2005), 165–196.
[27] Kerstin Ruhlrand, Christopher E Peters, Sean Andrast, Jeremy B Badler, Norman Badler, Michael Gleicher, Bilge Mutlu, and Rachel McDonnell. 2015. A review of eye gaze in virtual agents, social robotics and hci: Behaviour generation, user interaction and perception. In Computer graphics forum, Vol. 34. Wiley Online Library, 299–326.
[28] Najmeh Sadoughi, André Pereira, Rishub Jain, Iolanda Leite, and Jill Fain Lehman. 2017. Creating prosodic synchrony for a robot co-player in a speech-controlled game for children. In 2017 12th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 91–99.
[29] Joe Saunders, Hagen Lehmann, Yo Sato, and Christopher L Nehaniv. 2011. Towards using prosody to scaffold lexical meaning in robots. In 2011 IEEE International Conference on Development and Learning (ICDL), Vol. 2. IEEE, 1–7.
[30] Lue Steels. 2003. Evolving grounded communication for robots. Trends in cognitive sciences 7, 7 (2003), 308–312.
[31] Stefanie Tellex, Nakul Gopalan, Hadas Kress-Gazit, and Cynthia Matuszek. 2020. Robots that use language. Annual Review of Control, Robotics, and Autonomous Systems 3 (2020), 25–55.
[32] Greet Van de Perre, Haong-Long Cao, Albert De Beir, Pablo Gómez Estebe, Dirk Lefeber, and Bram Vanderborght. 2018. Generic method for generating blended gestures and affective functional behaviors for social robots. Autonomous Robots 42, 3 (2018), 569–580.
[33] Andrew D Wilson and Sabrina Golonka. 2013. Embodied cognition is not what you think it is: Frontiers in psychology 4 (2013), 58.
[34] Margaret Wilson. 2002. Six views of embodied cognition. Psychonomic bulletin & review 9, 4 (2002), 625–636.
[35] Yang Xiao, Zhijun Zhang, Aryel Beck, Junsong Yuan, and Daniel Thalmann. 2014. Human–robot interaction by understanding upper body gestures. Presence: Teleoperators and virtual environments 23, 2 (2014), 133–154.
[36] Youngwoo Yoon, Woo-Ri Ko, Minsu Jang, Jaeyeon Lee, Jaehong Kim, and Geehyuk Lee. 2019. Robots learn social skills: End-to-end learning of co-speech gesture generation for humanoid robots. In 2019 International Conference on Robotics and Automation (ICRA). IEEE, 4303–4309.