The Automatic Annotation of the Semiotic Type of Hand Gestures in Obama's Humorous Speeches

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Abstract

This paper describes a pilot study act to investigate the semiotic types of hand gestures in video-recorded speeches and their automatic classification. Gestures, which also comprise e.g. head movements and body posture, contribute to the successful delivery of the message by reinforcing what is expressed by speech or by adding new information to what is uttered. The automatic classification of the semiotic type of gestures from their shape description can contribute to their interpretation in human-human communication and in advanced multimodal interactive systems. We annotated and analysed hand gestures produced by Barack Obama during two speeches at the Annual White House Correspondent Dinners and found differences in the contexts in which various hand gesture types were used. Then, we trained machine learning algorithms to classify the semiotic type of the hand gestures. The F-score obtained by the best performing algorithm on the classification of four semiotic types is 0.59. Surprisingly, the shape feature that contributes mostly to classification is the trajectory of the left hand. The results of this study are promising, but they should be tested on more data of different type, produced by different speakers and in more languages.

Keywords: Multimodal Communication, Automatic Classification, Hand Gestures

1. Introduction

In face-to-face communication, people express their message both through the auditory modality, speech, and the visual modality, gestures, which comprise head movements, body postures and hand gestures. Co-speech gestures are not redundant and contribute to the delivery of the message by reinforcing what it is said or providing new content (McNeill, 2005; Kendon, 2004). Although the number of audio- and video-recorded speeches and conversations on the internet is growing every day, there is still a lack of freely available multimodally annotated data of different types of face-to-face communication. Since the manual annotation of gestures is extremely resource consuming, it is vital to address not only the automatic identification of occurrences of gestures and their physical characteristics, but also their interpretation. The automatic identification of hand gestural units from videos has been addressed by numerous studies, but identifying gestures from all kinds of videos is still not possible, and for this reason many studies use tracking devices or pose particular restrictions to lighting and settings of the videos (Keskin et al., 2011). Therefore, there is still a need to identify the function of gestures automatically, and distinguishing their semiotic type is a first step toward their interpretation which should also include the context in which the gestures are performed.

This paper presents a pilot work aimed to the automatic classification of the semiotic type of hand and arm gestures in two speeches of Barack Obama using coarse-grained descriptions of the gestural shape. An analysis of hand gesture types in these data is also provided. The two humorous speeches were held at the Annual White House Correspondents' Association Dinner in 2011 and in 2016. Obama's speeches are interesting because he is an excellent speaker and his ability in presenting his message in a clear and convincing way has been praised by both press corps and researchers, e.g. (Cooper, 2011). The video-recordings of these speeches are freely available on the internet and can be shared, according to the U.S.A. legislation, since they were transmitted by news channels.[1]

The article is organized as follows. In section 2., we shortly discuss background literature. In section 3., we describe the speeches and their annotations. Then, we present an analysis of the shape and semiotic types of the hand gestures based on these annotations (section 4.), and in section 5. we account for our machine learning experiments and their results. Finally, we evaluate and discuss the results of the analysis and classification experiments, and we suggest future work (section 6.).

2. Background Literature

Communicative gestures are temporally, semantically and pragmatically related to speech (McNeill, 1992; McNeill, 2005). These gestures are known as co-speech gestures and have several and often co-occurring functions. Researchers have shown that speech and gestures influence each other in different ways. For example, there is a relation between gesture and the syntactic structure of speech (McNeill, 1992), intonation (Loehr, 2004; Loehr, 2007) and lexical retrieval (Krauss et al., 2000).

Various categories of gestures have been proposed in the literature, inter alia (Ekman and Friesen, 1969; W.M.Wundt, 1973; Nespoulous and Lecours, 1986; McNeill, 1992; McNeill, 2005; Allwood et al., 2007) and the relation between types of gesture and their function has also been pointed out by for example Kendon (2004). In this work, we use the semiotic categories proposed by Peirce (1931) which were adopted in the MUMIN annotation framework (Allwood et al., 2007). The classification distinguishes three main categories *indexical*, *iconic* and *symbolic* gestures. In-

[1] The annotations of the speeches will be made available via the Danish CLARIN infrastructure.

dexical gestures have a direct connection with the objects which they denote and they comprise *deictic* gestures, also known as pointing gestures, and *non-deictic* gestures such as displays and beats. Beats are also known as batonic gestures and in these data all indexical non-deictic gestures are beats. Iconic gestures denote their objects by similarity and include *metaphoric* gestures. An example of iconic gesture is the quick alternating movement of index and middle fingers referring to a running event. An example of the metaphoric subclass of iconics is shown in Figure 1 a snapshot from *Speech16* that shows Obama making a grasping both-hands gesture in front of his chest while uttering *feel the burn*, the slogan of Bernie Sanders' campaign as democratic president candidate.

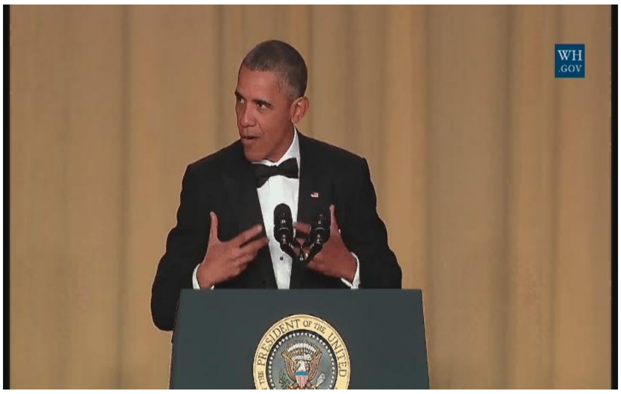

Figure 1: Metaphoric Gesture Co-occurring with the Speech Segment *feel the burn*

Finally, symbolic gestures, also called emblems, are conventionalized signs which are culture dependent. A symbolic gesture is for example the victory sign, in which the spread index and third finger resemble the letter *V*. The distinction between iconic and symbolic gestures is not always clear-cut as accounted for in the so-called Kendon's continuum (McNeill, 1992; Kendon, 2004). Furthermore, gestures often belong to more semiotic types at the same time since they are multifunctional (Allwood et al., 2007).
The automatic identification of hand gestures has been investigated in order to provide the automatic interpretation of sign languages (Keskin et al., 2011; Gebre et al., 2014), or to identify hand gestural units and their placement in the gestural space (Schreer et al., 2014). Better results have been obtained using tracking devices of different type (Keskin et al., 2011; Alexanderson et al., 2016). The present work uses coarse grained manual annotations of the shape and semiotic type of hand gestures.

3. The Data

Our data consists of the annotations of two audio- and video-recorded speeches by Barack Obama at the the 2011 and 2016 Annual White House Correspondents' Association Dinner. The speeches are called *Speech11* and *Speech16* in what follows.
During the Annual White House Correspondents' Association Dinners, the U.S.A. president holds a speech in which he makes fun of himself, his wife, his collaborators and political adversaries. Several recordings of these speeches are available on the internet (YouTube). We used the official recordings of the White House, which were available at `http:\www.WH.gov` while Obama was president. Obama was video-recorded frontally as is shown in Figure 2 and 3 which are snapshots from the two talks.

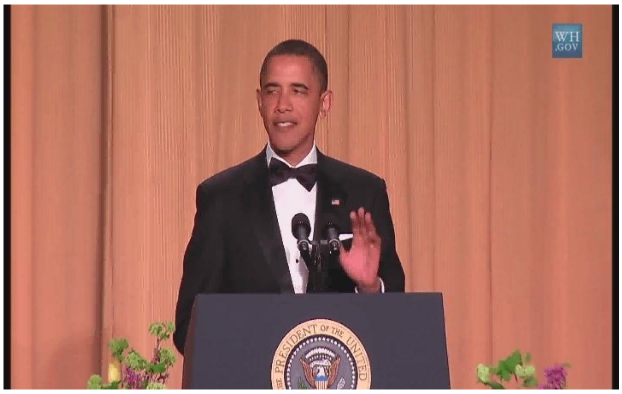

Figure 2: Snapshot from the 2011 Speech

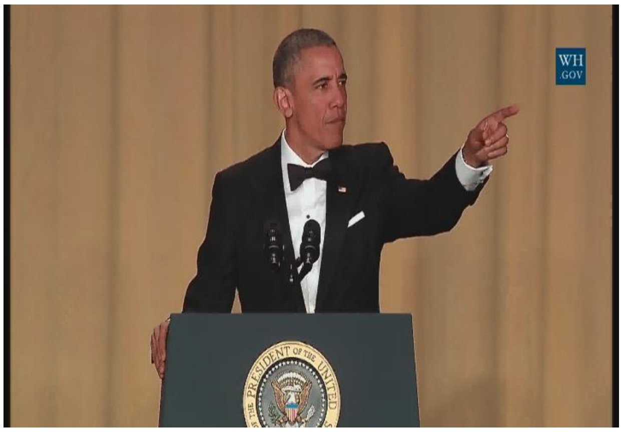

Figure 3: Snapshot from the 2016 Speech

Obama' s speech and audience reaction were transcribed reusing existing transcriptions of the talks from newspapers. The transcriptions comprise voiced segments, silent and filled pauses, and audience responses in the form of cheers, laughter and/or applause. The gestures of Obama were manually annotated in the ANVIL tool (Kipp, 2004). The video segments annotated in *Speech11* have a duration of 13 minutes and 22 seconds while the annotations of the *Speech16* video segments cover 30 minutes. In order to calculate the ratio hand gesture per second, we excluded the time during which Obama did not move his hands because the audience were laughing and/or applauding. The resulting data duration is 8 minutes for *Speech11* and 19 minutes for *Speech16*. A description of the annotation of the speeches and a study of the relation between speech pauses, gestures and audience response is in (Navarretta, 2017). The semiotic types of hand gestures were annotated for this study by one annotator (the author of the paper), and the annotations have been revised by the same annotator after several months. The Cohen' s kappa-score (Cohen, 1960) for intra-coder agreement on the two annotations is 0.85.

The shape and semiotic type features of gestures follow the MUMIN annotation framework (Allwood et al., 2007). The shape features which are relevant for the present study are in the first six rows of Table 1 and are a subset of the features proposed in (McNeill, 1992). The seventh and last row of the table contains the semiotic types which are used in these study. Many gestures belong to more semiotic types at the same time. For example, many deictic and iconic gestures are also beats. We have only annotated the most specific semiotic type and therefore beat gestures are only coded when the gestures do not also fall under another category. We only found five metaphorical iconic gestures and therefore we did not distinguish them from the other iconic gestures in the machine learning experiments. In the videos, we also annotated non communicative hand gestures such as Obama touching the cuffs of his shirt. These gestures are often called *adaptors* (Ekman and Friesen, 1969). The annotations of these gestures are not included in this study.

Attribute	**Value**
Handedness	BothHandsSym, BothHandsAsym, RightSingleHand, LeftSingleHand
HandRepetition	Single, Repeated
Fingers	IndexExtended, ThumbExtended, AllFingersExtended, FingersOther
TrajectoryLeftHand	LeftHandForward, LeftHandBackward, LeftHandSide, LeftHandUp, LeftHandDown, LeftHandComplex, LeftHandOther
TrajectoryRightHand	RightHandForward, RightHandBackward, RightHandSide, RightHandUp, RightHandDown, RightHandComplex, RightHandOther
PalmOrientation	PalmUp, PalmDown, PalmSide, PalmVertical, PalmOther
SemioticType	IndexicalDeictic, IndexicalNonDeictic, Iconic, Symbolic

Table 1: Shape and Semiotic Features of Hand Gestures

4. Data Analysis

The total number of the communicative hand gestures performed by Obama in the speeches is 298, that is he produces 0.18 hand gestures per second. Obama produces significantly less hand gestures in *Speech11* than in *Speech16*. More specifically, he produces 59 hand gestures (0.12 gestures per second) in *Speech11* and 239 hand gestures (0.21 gestures per second) in *Speech16*. The difference is significant: Chi square equals 13.2905, df=1, and $p = 0.000267 < 0.001$.

Table 2 shows the relation between handedness and semiotic types in these data. In the speeches, Obama performs more often gestures with his right hand than with his left hand or both hands. The second most frequently performed hand gestures are both-hands, and only one out of the 97 both-hands gestures is asymmetric. This asymmetric gesture is iconic. Not surprisingly, the most common semiotic types of hand gestures performed by Obama in the two speeches are indexical deictic and indexical non-deictic. The frequency of deictic gestures is specific to these humorous speeches in which Obama often points at individuals in the audience. Deictic gestures are performed with both hands and one hand, and the qualitative analysis of the data shows that the choice of the hand in one-hand deictics mostly depends on the physical position of the people at whom Obama points. If the people sit on his right side, he often uses his right hand, while he uses his left hand in the opposite case. Obama points with both hands at groups of people, or while referring to persons or objects not in the room. This also includes reference to abstract entities. In some cases he also points at himself with both hands. An interesting finding is that when gestures co-occur with a sentence containing a negation Obama uses his left hand or both hands.

Handedness	Dei	NonDeic	Icon	Symb	Total
BothHSym	21	47	27	1	96
RightH	67	30	15	6	118
LeftHand	36	30	13	2	81
BothHAsym	0	0	1	0	1
Total	125	107	56	11	298

Table 2: Handedness and Semiotic Types

Obama performs exactly the same number of indexical non-deictic hand gestures (beats) with his right and left hand, and the largest number of beats is produced with both hands.

Table 3 shows the percentage of repeated hand gestures for each of the categories in Table 2. Only 18% of the hand gestures produced by Obama are repeated, and not surprisingly, the most frequently repeated hand gesture type is Indexical Non-deictic (beat) followed by Iconic. The table also shows that Obama repeats more often both-hands and left-hand gestures (22% and 21% of the occurrences respectively) than right-hand ones (5% of occurrences).

Handedness	Dei	NonDeic	Icon	Symb	Total
BothHSym	5%	25%	31%	0	22%
RightHand	7%	3%	13%	0	5%
LeftHand	6%	37%	31%	0	21%
BothHAsym	0	0	0	0	0
Total	6%	30%	25%	0	18%

Table 3: Repetition and Semiotic Types

5. Classifying the Semiotic Types of Hand Gestures

The aims of our machine learning experiments were to determine a) to what extent the shape features of hand gestures are useful to train classifies to distinguish the semiotic type of hand gestures, b) which classifiers perform best on these data, and c) which shape features contribute mostly to classification. The shape features and the semiotic types used in the machine learning experiments are those in Table 1 with one exception: We merged the two categories BothHandsSymmetric and BothHandsAsymmetric since there was only one occurrence of asymmetric hand gestures in the data.

The machine learning experiments were run in WEKA (Witten and Frank, 2005). The algorithms which we tested are a support vector classifier (SMO), Naive Bayes, Bayes Network, Simple Logistic, LBR, LMT, Random Forest and a Multilayer Perceptron with backpropagation. The results of the classifiers were validated with ten-fold cross-validation, and are reported as Precision (P), Recall (R) and weighed F-score, which is calculated according to the following equation:

$$F1 = \frac{2 \times P \times R}{P + R}. \quad (1)$$

A majority classifier, which always chooses the most frequently occurring semiotic type, is the baseline. In the first group of experiments, we trained the classifiers on all features, and the results of these experiments are in Table 4. All algorithms performed significantly better than the base-

Algorithm	P	R	F
Baseline	0.18	0.42	0.25
Bayes Network	**0.59**	**0.6**	**0.59**
Naive Bayes	0.58	0.6	0.59
LBR	0.58	0.6	0.59
SMO	0.56	0.58	0.57
LMT	0.55	0.58	**0.56**
Simple Logistic	0.55	0.58	0.56
Random Forest	0.52	0.54	0.52
Multilayer Perceptron	0.53	0.53	0.53

Table 4: Classification of Hand Gestures

line. Significance was measured with paired corrected t-test and significance level $p < 0.001$. The classifier which performed best is Bayes Network (F-score 0.59) although Naive Bayes and LBR obtained the same F-score, and recall while they gave a slightly worse precision (the difference between the results of the three classifiers is not statistically significant). LMT and SMO obtained an F-score of 0.57 and 0.56 respectively, while the F-score of the Multilayer Perceptron is 0.53 and of Random Forest is 0.52 (the difference with respect to the results of the Bayes Network classifier are statistically significant at significance level $p < 0.01$).

The confusion matrix obtained with the Bayes Network classifier is given in Table 5. The confusion matrix shows that the classes which are identified more correctly are

a	b	c	d	classified as
21	25	1	9	a = Iconic
14	60	1	32	b = IndexicalNon-deictic
0	3	0	6	c = Symbolic
2	25	1	98	d = IndexicalDeictic

Table 5: Confusion Matrix of Bayes Network Trained on All Shape Features

IndexicalDeictic and IndexicalNon-deictic which are the most frequently occurring classes in the data. All symbolic gestures, which are seldom in this data, are classified incorrectly.

Attribute selection performed in WEKA with the *CfsSubsetEval*[2] applying the *BestFirst* method suggests HandRepetition, Fingers, Trajectory-Left-Hand and Trajectory-Right-Hand as the best features for classifying the semiotic type of hand gestures. To test how each feature contributes to classification, we performed a second group of experiments in which we trained Bayes Network classifier, the best performing classifier when the training set contains all features, on one shape feature at a time. The results of these experiments are in Table 6. The Bayes Network clas-

Features	P	R	F
all	0.59	0.6	0.59
Handedness	0.39	0.51	0.43
HandRepetition	0.41	0.5	0.41
Fingers	0.44	0.49	0.43
LeftHandTrajectory	**0.49**	**0.52**	**0.5**
RightHandTrajectory	0.45	0.48	0.42
PalmDirection	0.25	0.38	0.27

Table 6: Feature Contribution to Bayes Network Classification

sifier performs best when trained on the trajectory of the left hand, and this is a bit surprising since it is not the most common feature in the dataset. Information about handedness is the feature that gives the second best results. Also information about which fingers are involved in the gestures, the trajectory of the right hand and whether the gesture is single or repeated are useful when identifying the semiotic types of hand gestures. The feature that contributes less to the identification of the semiotic types of hand gestures is that describing the direction of the palm.

Table 7 shows the confusion matrix of the Bayes Network classifier trained on the trajectory of the left hand. As it can be seen from Table 7 and 5 that the classifier's performance decreases for all classes compared to the results of the same classified trained on all shape features. The worse results are those obtained for iconic gestures. This is not surprising since they are often produce with both hands.

Table 8 is the confusion matrix of the Bayes Network clas-

[2]The CfsSubsetEval calculates the predictive ability of each feature and considers the degree of redundancy among subsets of features.

a	b	c	d	classified as
11	26	0	19	a = Iconic
17	50	0	40	b = IndexicalNon-deictic
1	0	0	8	c = Symbolic
1	30	0	95	d = IndexicalDeictic

Table 7: Confusion Matrix of Bayes Network Trained on Left Hand Trajectory

sifier trained on the Handedness feature. IndexicalNon-deictic and IndexicalDeictic are the two classes which are identified best while all iconic and symbolic gestures are wrongly classified when the Bayes Network classifier is trained on the feature Handedness.

a	b	c	d	classified as
0	28	0	28	a = Iconic
0	47	0	60	b = IndexicalNon-deictic
0	1	0	8	c = Symbolic
0	22	0	104	d = IndexicalDeictic

Table 8: Confusion Matrix Bayes Network Trained on Handedness

6. Discussion and Future Work

Obama produces significantly more hand gestures in *Speech16* than in *Speech11* and the most frequently produced hand gestures in the two speeches are the pointing gestures (Indexical Deictic in our classification). The frequency of gestures pointing at individuals in the audience are typical of these speeches since Obama makes fun, greets or praises persons in the audience while he points at them. The second most common hand gestures are beats (IndexicalNon-deictic), but nearly all other gestures have a batonic component.

With respect to handedness,most of Obama's hand gestures are right-hand or both-hands gestures. All both-hands gestures in these data are symmetric a part from one asymmetric iconic gesture. Under 20% of the hand gestures produced by Obama are repeated and the most frequently repeated hand gesture types are IndexicalNon-deictic and Iconic. With respect to handedness, repetition mostly involves both-hands gestures (22% of the occurrences) and left-hand gestures (21% of the occurrences) while right-hand gestures are only repeated in 5% of their occurrences.

The qualitative analysis of the data shows that Obama often points at persons in the room with the hand that is on the same side as these persons in the room. Thus, Obama points with his left hand at people sitting in the left part of the room with respect to him and with his right hand at people sitting on his right side. Obama often uses both hands or his left hand when referring to objects or people not present in the room and when his hand gesture refers to abstract objects.

Hand gestures co-occurring with and related to utterances or fragments of speech which contain a negation are both-hands or left-hand. Whether these findings reflect a general tendency in Obama's speeches should be investigated on more data.

The results of our machine learning experiments aimed to automatically classify the semiotic type of hand gestures from their shape features show that the best performing algorithm on these data is Bayes Network which obtained an F-score of 0.59. All the classifier we tested gave significantly better results than the majority classifier which always chooses deictic as the semiotic type of the gestures. The worse performance was obtained by a Random Forest classifier and a Multilayer Perceptron with backpropagation probably because of the limited size of the data.

The results of classification confirm that there is a relation between form and function of hand gestures (Kendon, 2004) and, not surprisingly, they also indicate that gestures can only to some extent be interpreted on the basis of their form. In some cases, they must be interpreted in the context in which they occur since gestures can be ambiguous as words. For example, forming a circular shape with the thumb and the index finger can be in the same culture the *OK* symbol, or can refer to a round object, a ring, the number zero etc. Moreover, in our experiments we did not distinguish the metaphoric subclass of iconic gestures, even though this information is available in the annotations, because there were too few metaphoric gestures in the data. Furthermore, the content of speech must be used to distinguish metaphoric gestures from generic iconic gestures, while in our machine learning experiments we only included shape descriptions of the gestures.

In the second group of experiments, we tested which features contribute mostly to classification, and the results of these experiments show that training the Bayes Network classifier on data annotated with the trajectory of the left hand gives the best results. This is surprising since the trajectory of the left hand is not the most frequent feature in the data. The reason for this can be that the three most common semiotic types (IndexicalDeictic, IndexicalNon-deictic and Iconic) are more equally distributed over the left-hand trajectory feature than in the other features. Also information about handedness, the trajectory of the right hand, the position of the fingers and whether the gestures are repeated or not gave good results, while information about the direction of the palm is the feature that contributed less to classification. Since the position of the palm changes during many hand gestures, the value of this feature only refers to the direction of the palm at the gestural stroke. This might well be the reason why this feature is not very useful for identifying the semiotic type of hand gestures.

The results of our machine learning experiments are promising since only few general shape features were used as training data. However, the shape and form of hand gestures were annotated manually and therefore classification should also be tested on automatically produced shape annotations, and on more fine-grained annotations. Furthermore, some types of gesture are culture specific and there is a great variation in the way gestures are produced by different subjects (Kendon, 2004; Navarretta, 2012). It must also be noted that in the two speeches Obama is reading from a manuscript and he produces very clear hand ges-

tures, which is not necessarily the case for other individuals or in other communicative situations. Therefore, the classification of semiotic types of hand gestures should also be applied to gestures performed by other subjects in other contexts and cultures. The classification experiments could also be tested on other gesture types, such as head movements and body posture.
A future direction of research could also be considering the form of the hand during the gestures, using a kind of hand gesture lexicon as proposed e.g. in (Poggi and Caldognetto, 1997) and (Kipp, 2004).

7. Bibliographical References

Alexanderson, S., House, D., and Beskow, J. (2016). Automatic annotation of gestural units in spontaneous face-to-face interaction. In *Proceedings of the Workshop on Multimodal Analyses Enabling Artificial Agents in Human-Machine Interaction*, MA3HMI '16, pages 15–19, New York, NY, USA. ACM.

Allwood, J., Cerrato, L., Jokinen, K., Navarretta, C., and Paggio, P. (2007). The mumin coding scheme for the annotation of feedback, turn management and sequencing. *Multimodal Corpora for Modelling Human Multimodal Behaviour. Special Issue of the International Journal of Language Resources and Evaluation*, 41(3–4):273–287.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, 20(1):37–46.

Cooper, M. M. (2011). Rhetorical agency as emergent and enacted. *College Composition and Communication*, 62(3):420–449.

Ekman, P. and Friesen, W. V. (1969). The repertoire of nonverbal behavior: Categories, origins, usage, and coding. *Semiotica*, 1(1):49–98.

Gebre, B. G., Crasborn, O., Wittenburg, P., Drude, S., and Heskes, T. (2014). Unsupervised Feature Learning for Visual Sign Language Identification. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (ACL 2014)*, pages 370–376. ACL.

Kendon, A. (2004). *Gesture: Visible Action as Utterance*. Cambridge University Press.

Keskin, C., Aran, O., and Akarun, L. (2011). Hand gesture analysis. In Albert Ali Salah et al., editors, *Computer Analysis of Human Behavior*, pages 125–149. Springer London, London.

Kipp, M. (2004). *Gesture Generation by Imitation - From Human Behavior to Computer Character Animation*. Ph.D. thesis, Saarland University, Saarbruecken, Germany, Boca Raton, Florida, dissertation.com.

Krauss, R., Chen, Y., and Gottesman, R. F. (2000). Lexical gestures and lexical access: a process model. In D. McNeill, editor, *Language and gesture*, pages 261–283. Cambridge University Press.

Loehr, D. P. (2004). *Gesture and Intonation*. Ph.D. thesis, Georgetown University.

Loehr, D. P. (2007). Aspects of rhythm in gesture and speech. *Gesture*, 7(2):179–214.

McNeill, D. (1992). *Hand and Mind: What Gestures Reveal About Thought*. University of Chicago Press, Chicago.

McNeill, D. (2005). *Gesture and thought*. University of Chicago Press.

Navarretta, C. (2012). Individuality in Communicative Bodily Behaviours. In A. Esposito, et al., editors, *Behavioural Cognitive Systems*, volume 7403 of *Lecture Notes in Computer Science*, pages 417–423. Springer Verlag, Berlin Heidelberg.

Navarretta, C. (2017). Barack Obama's pauses and gestures in humorous speeches. In *Proceedings of the 4th European and 7th Nordic Symposium on Multimodal Communication (MMSYM 2016), Copenhagen, 29-30 September 2016*, number 141 in Linköping University Conference Proceedings, pages 28–36. Linköping University Electronic Press, Linköpings universitet.

Nespoulous, J.-L. and Lecours, A. (1986). Gesture: Nature and function. In J.-L. Nespoulous, et al., editors, *The Biological Foundations of Gestures: Motor and Semiotic Aspects*, chapter 2, pages 49–62. Lawrence Erlbaum Association, Hillsdale,N.Y.

Peirce, C. S. (1931). *Collected Papers of Charles Sanders Peirce, 1931-1958, 8 vols*. Harvard University Press, Cambridge, MA.

Poggi, I. and Caldognetto, E. (1997). *Mani che parlano*. Unipress, Padova.

Schreer, O., Masneri, S., Skomroch, H., and Lausberg2, H. (2014). Coding Hand Movement Behavior and Gesture with NEUROGES Supported by Automatic Video Analysis. In A.J. Spink, et al., editors, *Proceedings of Measuring Behavior 2014,*, August.

Witten, I. H. and Frank, E. (2005). *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann, San Francisco, second edition.

W.M.Wundt. (1973). *The language of gestures*. Mouton.