The coding and annotation of multimodal dialogue acts

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Abstract

This paper describes how the ISO 24617-2 annotation scheme can be used, together with the DIT++ method of ‘multidimensional segmentation’, to annotate nonverbal and multimodal dialogue behaviour. We analyse the fundamental distinction between (a) the coding of surface features; (b) form-related semantic classification; and (c) semantic annotation in terms of dialogue acts, supported by experimental studies of (a) and (b). We discuss examples of specification languages for representing the results of each of these activities, showing how dialogue act annotations can be attached to XML representations of functional segments of multimodal data.

Keywords: multimodal dialogue behaviour, multimodal dialogue act annotation, international standards

1. Introduction

Recent years have witnessed a growing interest in annotating linguistic data at the semantic level, including the annotation of dialogue corpus data. Various annotation schemes have been developed for dialogue act annotation, of which DAMSL (Dialogue Act Markup using Several Layers, Allen and Core (1997)) is perhaps the most widely used. The DIT++ scheme (Bunt, 2006; 2009) combines the multidimensional DIT scheme (Bunt, 1994) with concepts from DAMSL and various other schemes, providing precise definitions for its communicative functions and dimensions. This scheme has been the basis for defining the international standard for dialogue act annotation ISO 24617-2. This annotation scheme is designed in such a way that it can be applied not only to spoken dialogue, as is the case for most of the previously defined dialogue annotation schemes, but also to multimodal dialogue, as shown in this paper.

Before going into the details of multimodal dialogue act annotation, we first discuss the fundamentals of ‘coding’ (or ‘transcribing’) and ‘annotating’ multimodal dialogue behaviour, making a clear distinction between the two (Section 2). We subsequently discuss practical aspects of transcription, segmentation and annotation processes. We report on a series of coding experiments, performed in order to measure the reliability of human codings, and compare these with automatic coding reliabilities reported in the literature. Section 3 describes the coding of multimodal dialogue behaviour in terms of low-level surface features of body movements. Section 4 addresses the form-related classification of visible movements by humans and machines. Section 5 discusses the multidimensional segmentation and annotation of multimodal data using the ISO 24617-2 dialogue act annotation scheme. Section 6 presents the XML-based representation of multimodal dialogue data, using the Dialogue Act Markup Language (DiAML) defined in ISO 24617-2. Section 7 concludes the paper with a brief look back and a look forward to future work in this area.

ISO Draft International Standard DIS 24617-2:2010 has been accepted as an ISO standard in January 2011.

2Detailed information about the MapTask project can be found at http://www.hrcc.ed.ac.uk/maptask/
3Augmented Multi-party Interaction, for more information visit http://www.amiproject.org/
4For more information about the TRAINS corpus please visit http://www.cs.rochester.edu/research/speech/trains.html
5For more information and downloads visit http://praat.org
6Difference between the time that a turn starts and the moment that the previous turn ends.
behavioural features, such as changes in muscular activity (body parts involved and form of movement), or direction, trajectory and speed of movements. For example, the Facial Action Coding System (FACS)\(^7\) codes facial expressions describing muscular activities that produce changes in facial appearance. HamNoSys\(^8\) is a transcription system for coding hand gestures by describing shape, direction, speed, length and form of movement, hands orientation and location. The CoGest scheme (Gut et al., 2003) proposes a feature-based vector notation where a gesture is represented by a set of values of gesture attributes like source, trajectory, target, and shape of trajectory. For example, the CoGest string 15m,5A,ri,ci,1B,l,r(0),me,15m,5A,rp describes an unrepeatet gesture carried out with medium speed with the right hand tracing a large circle with a pointed index finger, which starts and ends with the hands on the lap.

Other schemes use types of movement as labels, e.g. nod or shake for the head (e.g. MUMIN, Allwood et al., 2004) or iconic, morphetic, adaptor for the hand (e.g. Kipp, 2004). Still others immediately assign a high-level semantic interpretation to observed movements, e.g. concordance signal, negative signal, turn signal (see the e.g., AMI Guidelines for Individual Actions Annotation, 2005).

The transcription of the movements of dialogue participants in terms of pragmatic meaning is risky for several reasons. First of all, the meanings that different movements may convey should be established empirically, rather than a priori. There are too many different possible body movements and facial expressions with considerable cultural and even individual variation to be able to judge their meaning unequivocally as part of a transcription scheme. The characterisation of movements in terms of surface features, by contrast, allows their interpretation to be tested empirically, determining e.g. which behaviour means disbelief, agreement or puzzlement. In other words, description should be separated from interpretation. Similar considerations apply to the automatic generation of communicative behaviour. When behaviour with certain functional meaning is to be produced, we need to know what behavioural features correspond to this type of behaviour.

Second, manual coding is expensive. Automatic speech recognizers can be used for the production of speech transcriptions (with manual correction of the output). Automatic detection and coding of visible movements either from video or from direct observation is an active research field with applications in a range of domains such as virtual reality, ‘smart’ surveillance systems, advanced user interfaces, motion analysis, and robotics. The state of the technology for markerless motion capture is mature enough to boost the research on the recognition of action units using off-the-shelf and affordable equipment, such as webcams for facial expression tracking (Dornaika and Davoine, 2006; Dornaika and Raducanu, 2009), and depth sensing devices for full-body tracking (Shotton et al., 2009). In this area, description and interpretation are distinguished clearly. The standard procedure goes as follows:

1. sensors capture any noticeable motions, and low-level features are derived and selected, such as parts of body moved, relative and absolute positions, angles, velocity, periodicity, and intensity. Lösch (2006) extracted for example 320 features from the body model which is provided by the tracking system;

2. potential action spotting: segmentation of the data stream into temporal regions that might correspond to actions or transitions from one action to another (see e.g. Stiefmeier and Roggen, 2007);

3. semantic interpretation: classification of action units, associating motion segments with categories of a knowledge base, e.g. pointing gesture, smile, kissing, or shaking hands, or identifying an unknown motion pattern through classification procedures such as HMMs (Ahmad and Lee, 2006), DTW (Kang et al., 2006), or SVM (Ramanan and Forsyth, 2003);

4. pragmatic interpretation, e.g. in terms of communicative functions such as agreement, or in terms of communicative function qualifiers (see Section 4) such as uncertainty, anger, happiness, surprise, or fear (De la Torre and Cohn, 2011).

The most recent approaches tend to merge the stages of segmentation and classification, i.e. to segment while classifying (see Unzueta and Goenxtxea, 2010; Zhou et al., 2011). This speeds up the action recognition process as a whole. On such an approach there is no segmentation without the classification of units, since the identification of action unit boundaries depends on how an action unit is defined. While the combination of segmentation and annotation has practical advantages, the distinction between description or coding\(^9\) and annotation is methodologically very important. Coding is the representation of speech, sound, or movement using a certain coding system, e.g. phonetic or orthographic transcriptions for speech, and representation for physical realization of body and facial actions. For the latter, a variety of markup languages have been created, such as the Virtual Human Markup Language (VHML)\(^10\) and the Multimodal Utterance Markup Language (MURML, Kranstedt et al., 2002). The Behaviour Markup Language (BML) developed within the SAIBA\(^11\) framework is a description language for controlling the verbal and nonverbal behaviour of virtual characters (see Kopp et al., 2006 and Vilhjalmsson et al., 2007). It describes

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\(^{7}\)For more information visit: \url{http://face-and-emotion.com/dataface/general/homepage.jsp}

\(^{8}\)For more information visit \url{http://www.sign-lang.uni-hamburg.de/projekte/hamnosys/hamnosyserklaerungen/englisch/contents.html}

\(^{9}\)Both terms are used in the literature. We prefer to use the term ‘coding’ since this term in our view better captures the essence of this process, namely, representation of perceived bodily actions using a specific notation system, e.g. feature vectors. Coding results in transcription.

\(^{10}\)See \url{http://www.vhml.org}

\(^{11}\)The Situation, Agent, Intention, Behavior, Animation framework specifies multimodal generation at a macro-scale, consisting of processing stages on three different levels: (1) planning of a communicative intent, (2) planning of a multimodal realization of this intent, and (3) realization of the planned behaviour. For more information please visit \url{http://www.mindmakers.org/projects/SAIBA}
the physical realization of behaviours and synchronization constraints. When extended properly with articulate specifications of the surface form of nonverbal behaviour, BML can also be used for coding human multimodal dialogue behaviour.

The term ‘annotation’ refers to the addition of linguistic information to segments of language data and/or nonverbal communicative behaviour (see the ISO Linguistic Annotation Framework, ISO 24612:2010), where linguistic information may be (morpho-)syntactic, semantic or pragmatic. As part of the ISO 24617-2 standard, the Dialogue Act Markup language (DiAML) for dialogue act annotation has been defined, which will be discussed in Section 6.

3. Obtaining reliable multimodal transcriptions: coding experiments

When we agree on the importance of the distinction between coding and annotation, and that the former should be performed in terms of behavioural surface features, the question arises what surface feature can be coded reliably. The coding of a movement normally consists of determining (i) body parts involved in the movement; (ii) temporal boundaries and duration of phases of a movement, where often three or four phases are considered: (1) the onset or preparation; (2) the peak, sometimes divided in two (a) stroke, (b) hold), and (3) offset (or retraction); (iii) spatial characteristics like angles, direction, trajectory, distance from and relative position to the rest of the body or specific other body parts, and size; and (iv) characteristics like velocity, periodicity and intensity.

Transcriptions of multimodal communicative behaviour are mostly obtained by employing trained transcribers. This method is expensive and as we will show not all features can be coded reliably by human transcribers. The CoGest scheme provides an elaborate coding system that includes coding of all the surface features for hand and arm gestures mentioned above. Gut et al. (2003) reported that the observed agreement on hand and arm gesture classification when applying the CoGest scheme was only 23.4%. The main source of disagreement was formed by categories like gesture boundaries, trajectory, size, speed and periodicity of movements. De la Torre et al. (2011) also noticed that average manual error compared to automatic temporal segmentation was within 10-12 frames for the movement offset, and 2 frames for the movement peak when coding facial expressions using FACS.

Jovanovic (2007) reported that coding the focus of attention as derived from head, gaze and posture observations can be done with a very high level of agreement and with very high precision: changes are marked in the middle of eye movements between old and new target with agreement (Krippendorf, 1995) between annotators ranging from 0.84 to 0.95. In order to assess the difficulties and possibilities in coding surface features reliably, we performed coding and evaluation experiments focusing on five forms of nonverbal expression: gaze direction, head movements, hand and arm gestures, posture shifts, and facial expressions.

Two scenario-based dialogues with a total duration of 51 minutes from the AMI corpus\(^\text{12}\) were selected. Orthographic transcriptions of the speech were produced semi-automatically (manually corrected output from an automatic speech recognizer). Transcriptions of the movements of each participant were performed fully manually. Transcribers were asked to segment the behaviour (assigning start and end times), and to code surface features such as what body part is involved in the action (head, hand, arm, upper body, lips, eyes, eyebrows, chin, nose, etc.), direction of movement (up, down, left, right, backward, forward); trajectory (e.g. line, circle, arch); distance from the body for hands (e.g. close to the body, in contact with the body); size (e.g. large, small, medium, extra large); velocity (slow, medium, fast); and periodicity (number of repetitions up to 20 times). For each movement intensity was determined: 0 - no movement; 1 trace (noticeable movement); 2 marked (significant evidence for a movement). The floor transfer offset (see footnote 6) and duration of a movement (in milliseconds) were computed automatically. The coding was thus in the line with the CoGest scheme.

The nonverbal behaviour of the dialogue participants was transcribed using video recordings for each individual participant, running them without sound to eliminate the influence of what was said. Transcriptions were performed using the ANVIL tool\(^\text{13}\), which allows transcriptions in separate tiers for each participant, using specific tiers for each type of movement (see Bunt, Kipp and Petukhova, 2012). Movements were transcribed by two coders in order to be able to judge the reliability of the coding. Inter-coder agreement was measured in terms of Cohen’s kappa. The major disagreements observed between coders concern (1) the definition of temporal boundaries (segmentation); (2) judgements of the velocity and intensity of movements; (3) determination of spatial characteristics such as size, trajectory and distance.

As for temporal segmentation, the difference between annotators ranged between 120 ms (up to ± 3 frames, e.g. for gaze re-direction) to 520 ms (up to ± 13 frames, for hand gestures because some neighboring locations may be quite subtle). In terms of kappa, the agreement reached here was moderate: .46. This is comparable with findings reported by De la Torre et al. (2011), discussed above. As for the velocity and intensity of movements, coders have genuine difficulty to judge these rather subjective and speaker-dependent characteristics when no or limited information about the dialogue participants is available. Coding does speed up and judgments are made with higher degree of certainty in the course of the coding process. Agreement between coders in terms of kappa for defining the speed of movements was .29, with differences per expression type: the highest when judging the speed of head nods (.49) and the lowest when judging the speed of facial activities, such as eyebrow or lip movements and blinking (.18). Finally, coders differed in opinion about movement intensity; in particular judgments about ‘no movement’ or ‘noticeable movement’ categories were often dissimilar, one annotator thinking that there was some trace of a movement, another

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\(^{12}\)See http://www.amiproject.org/

\(^{13}\)See http://www.dfk1.de/~kipp/anvil
not seeing any movement at all. Overall kappa was .41. As for spatial features, especially the size of movements is a rather subjective category, and a source of disagreement (kappa .38), with the lowest score for head movements (kappa .11) and the highest for hand and arm gestures (.57). Trajectory labeling caused some confusion (e.g., one coder sees an ellipsis, another a circle or arch), ranging from .36 for head to .21 for arm gestures and .09 for gaze direction. Judging distances, coders have less difficulty (kappa of .53), maybe because the participant’s body forms a clearer reference point.

Spatial characteristics of body movements are very important for their interpretation, since the same type of movement performed with different speed, amplitude or periodicity may have different communicative functions (see e.g. Petukhova and Bunt, 2010b). Temporal features are obviously of crucial importance for the synchronization of verbal and nonverbal behaviour, in particular when this is used for the generation of multimodal dialogue utterances. While human coding is seen not to be reliable, automatic techniques, by contrast, are quite robust, offering optimal precision, such annotations are useful for identifying and annotating the meaningful units in dialogue in terms of dialogue acts, resulting in more accurate and adequate analysis of dialogue behaviour, as we will discuss in the next two sections.

### Table 1: Cohen’s kappa scores for each type of visible movement reached by two coders.

| Type of expression     | Kappa |
|------------------------|-------|
| Gaze                   | .83   |
| Head movements         | .82   |
| Hand movements         | .48   |
| Facial expression      | .65   |
| Posture shifts         | .81   |

The main lesson to be learned here is that humans are generally not very successful in coding spatiotemporal characteristics of body movements reliably; machines are better at this task and can take this job over in the near future.

### 4. Form-related interpretation of visible movement: annotation experiments

Movements, transcribed as discussed in the previous section, can be assigned a meaning in terms type of movement. For example, an up and down head movement is a nod, a left to right head movement is a head shake, and elongating the lips and lifting the lip corners is a smile. Annotation of the type of transcribed movements allows the determination of variations (such as different spatial, temporal, durational and intensity qualities) in bodily activity that may have one and the same meaning. This information provides an empirical basis for precise semantic/pragmatic analysis, e.g. to establish whether one and the same type of movement but with different low-level characteristics may have the same or a slightly different communicative function, which is equally important for the interpretation of dialogue behaviour and for its generation.

To assess the reliability of human determination of type of visible movement, we performed an experiment for which a classification scheme was designed that combines the MUMIN scheme (Allwood et al., 2004) and the scheme provided with the ANVIL tool (Kipp, 2004), and makes some extensions. We defined 84 movement types: 2 for gaze, 9 for head movements, 40 for hand and arm movements, 24 for facial expressions and 9 for posture shifts. Coders were asked to also indicate their degree of certainty for each decision that they made, ranging from 0 (not certain at all) to 5 (very certain).

The experiments show that humans are good at action classification (see Table 1) and are quite certain in making such decisions (3.8 average degree of certainty). As a rule they do not experience any problems in identifying movement types.

Table 1 shows that the classification of arm and hand movements is a relatively difficult task. A major source of disagreement here was the classification of hand shapes, e.g. what one annotator sees as an open palm gesture with all fingers in joined position and bended, another sees all fingers joined except for the thumb, but not bended.

People have a richer experience and background knowledge for action classification than machines. Machines cannot operate directly in terms of form-related classes, but when provided with a sufficiently large variety of examples of one and the same type of movement, machines can learn this, as shown by Lösch et al., (2008) for teaching robots to perform certain types of action. When recognizing actions, the machine task is often just to identify similar surface patterns and mark them; the marked patterns are then classified by experts, and this information is fed back into the system for the next recognition iteration, this time in terms of action types (see e.g. Zhou et al., 2011).

The main conclusion from these experiments is that surface features of nonverbal behaviour can be interpreted reliably by human transcribers in terms of type of visible movement. Machines can use such annotations to learn to interpret movement features. Together with motion tracking features, which can be computed automatically with high precision, such annotations are useful for identifying and annotating the meaningful units in dialogue in terms of dialogue acts, resulting in more accurate and adequate analysis of dialogue behaviour, as we will discuss in the next two sections.

### 5. Segmentation and annotation of multimodal dialogue acts

Communication in multimodal dialogue is a complex activity. Figure 1 shows that dialogue participants most of the time perform some communicative activity. By re-directing his gaze from the working table to participant D, who is speaking, and shifting his posture to working position, participant B indicates that he is paying attention; by a short single head nod and lip movements he signals that he understood that D wants B to be the next speaker (D looks at B while asking a question) and accepts the turn.
Nonverbal behaviour may serve several purposes. It may emphasize or articulate the semantic content of a spoken dialogue act as shown in Figure 2 where the pointing gesture to the right cheek contributes to the semantic content of the verbal utterance *He kissed me*, specifying that the kiss was on the right cheek.

Nonverbal behaviour may emphasize or support the intended meaning of synchronous verbal behaviour. In the same example in Figure 2 the fact that the speaker was smiling indicates that he liked being kissed: *He kissed me on my right cheek and I liked it.*

Nonverbal behaviour may also perform separate dialogue acts in parallel to what is contributed by another participant. For instance, the majority of head nods signal positive feedback; gaze aversion often signals hesitation and turn keeping (see Figure 1).

Finally, nonverbal behaviour may express a separate dialogue act in parallel to what the same speaker is expressing verbally, adding to the multifunctionality of dialogue utterances. For instance, speech-focused movements accompanying content words (e.g. iconic gestures accompanying the search for a word), or body-focused movements like rubbing cheeks when searching for an elusive word, indicate that the speaker needs some time to gather his/her thoughts or to formulate an utterance, and is therefore stalling for time, while keeping the turn (see e.g. Petukhova and Bunt, 2010b).

All this has consequences for segmenting dialogue behaviour into units and assigning meaning to them. Where a functional segment in speech-only dialogue is a stretch of speech, in multimodal dialogue it is a complex structure, made up of stretches of communicative behaviour in each of the modalities that are used. Figure 1 illustrates this; participant D asks a question for clarification while directing his gaze to participant A (at whom he directs the question) and narrowing his eyes as visual support for conveying the intention to get something clarified. The multimodal functional segment in this case consists of the verbal segment “What’s teletext”, the stretch of gaze behaviour where D redirects his gaze to A, and the stretch of facial expression behaviour where he narrows his eyes. An attractive solution for how to identify meaningful multimodal dialogue units and specify their meaning accurately has been proposed in ISO standard 24617-2, based on the DIT multidimensional approach to segmentation and annotation of dialogue acts (see Geertzen et al., 2007). ISO 24617-2 defines a dialogue act as

(1) communicative activity of a participant in dialogue, interpreted as having a certain communicative function and semantic content.  

A communicative function specifies the way semantic content is to be used by the addressee to update his context model when he understands the corresponding aspect of the meaning of a dialogue utterance. For instance, head nods

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| Speaker | Observed communicative behaviour/ annotation |
|---------|---------------------------------------------|
| coding D | What’s teletext |
| gaze    | averted(table) |
| words   | person B |
| eyes    | narrow |
| posture | working position |
| annotation | SetQuestion |
| TurnM. | Turn assign to B |

| coding B | sim | a | British |
| words | It’s a British thing |
| gaze | averted(table) |
| head | short angle nod |
| lips | open, closed, open |
| posture | down |
| annotation | pos. attention |
| TurnM. | pos. execution |

**Figure 1:** Example of coding and annotating multimodal dialogue behaviour.

| Speaker | Observe communicative behaviour |
|---------|--------------------------------|
| A       | glance, head | relaxed |
| gaze    | forehead | averted |
| face    | eyebrows, half-raised |
| eyes    | narrowed, corners wrinkled |
| cheeks  | outer, upper area of cheeks raised |
| lips    | elongated, both corners up |
| chin    | no noticeable movement |
| part    | lower-arm, hand |
| Hand /arm | handness, right |
| Hand shape | pointing index finger |
| direction | up |
| trajectory | arch |
| location | check, right |
| velocity | medium |
| size    | large |
| intensity | significant |

**Figure 2:** Example of annotation of multimodal dialogue behaviour.

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14 A note, added to the definition, remarks that “A dialogue act may additionally have certain functional dependence relations, rhetorical relations, and feedback dependence relations.”
Speaker observed communicative behaviour

| Speaker | Observed communicative behaviour |
|---------|----------------------------------|
| P1      | speech | maybe we should have pause on the play button |
| P2      | head   | form direct to B all right trajectory shape blue velocity medium size |
|         | mouth  | significant formality |
|         | face   | expression constricted facial expression raised eye width, up, down cheek movement no noticeable movement lip full close, down eye raise eyebrow up |
|         | hand   | direction up trajectory shape line velocity medium size管控 intensity significant |

Figure 3: Example of coding multimodal dialogue behaviour.

(2) `<timeline unit="ms"
  <when xml:id="t1" absolute="297722"/>
  <when xml:id="t2" absolute="486737"/>
  ...
  <when xml:id="t9" absolute="1897215"/></timeline>

Verbal contributions, segmented into tokens (TEI-compliant)

- `<w xml:id="w1">Maybe</w>`
- `<w xml:id="w2">we</w>`
- ...
- `<w xml:id="w9">button</w>`

Dialogue act annotation is the assignment of functional meaning to stretches of dialogue behaviour. The unit in dialogue that carries a functional meaning is the functional segment, defined as a minimal stretch of behaviour that has a communicative function (Geertzen et al., 2007). This definition implies that the identification of functional segment boundaries cannot be an independent process: segmentation and annotation on this view are simultaneous, rather than consecutive processes. Note also that functional

The rule is: do not include material in a functional segment which does not contribute to its communicative function(s).
segments may be discontinuous, may overlap, may stretch over more than one turn, and may contain material contributed by different speakers.

The ISO 24617-2 taxonomy of communicative functions distinguishes 9 dimensions, addressing information about a certain task (the Task dimension); the processing of utterances by the speaker (Auto-feedback) or by the addressee (Allo-feedback); the management of difficulties in the speaker’s contributions (Own-Communication Management) or that of the addressee (Partner Communication Management); the speaker’s need for time to continue the dialogue (Time Management); the allocation of the speaker role (Turn Management); the structuring of the dialogue (Dialogue Structuring); and the management of social obligations (Social Obligations Management). Identifying meaningful dialogue segments by considering multiple dimensions simultaneously results in very accurate description of the intended meaning of dialogue utterances (see illustrative example in Figure 1, and Petukhova and Bunt, 2011). A multidimensional approach to segmentation and annotation moreover supports the identification of relevant dialogue segments not only per dimension but also per modality, and the identification of complex multimodal multifunctional segments. We will see below how these can be represented according to the ISO 24617-2 standard.

6. DiAML representation

ISO 24617-2 includes the specification of the XML-based Dialogue Act Markup Language DiAML for the representation of dialogue act annotations. This representation relies on a three-level architecture:

1. the level of primary data, which may for example be a speech recording, a written text, or a video clip;
2. the marking of functional segments either directly in the primary data, in a coding of it, or in a lower-level representation of the primary data, such as the output of a tokenizer or action classifier for body movements;
3. the annotation associated with a functional segment.

At level 1, the primary data can be encoded in accordance with the TEI guidelines (TEI P5, 2007). For example, for the dialogue fragment of Figure 3, the speech turns and movements can be transcribed with timing information and a specification of the speaker as in (2).

At level 2, functional segments can be identified by functionalSegment elements, which group together the components of multimodal communicative behaviour that constitute a multimodal functional segment. The example in Figure 3 of participant p2 turning his gaze to participant p1 (gaze1) and then averting it (gaze2), while producing the speech segment Maybe (vec2), performing a shoulder-shrug (hag1), constricting the forehead muscles (fh1), raising eyebrows (brow1), widening the eyes (eye1), lowering the lip corners (lip3) and raising the chin (chin1), can be represented as in (4):

At level 3, in the DiAML representation of the dialogue act annotations the @target attribute, which can denote any pointer reference, is used to point to the multimodal functional segment. Example (5) illustrates the use of DiAML for the dialogue fragment in Fig. 3, containing two multimodal functional segments, corresponding to two dialogue acts:

Note that the DiAML annotation contains only semantic information; the description of the functional segments is not part of the annotation, but of the coding.

7. Conclusions and Outlook

In this paper we have described an approach to multimodal dialogue act annotation, starting from the conceptual distinction between the ‘coding’ of observable multimodal dialogue behaviour and the ‘annotation’ of such behaviour in semantic and pragmatic terms, and supported by experimental results in human and automatic multimodal dialogue coding and annotation. We provided XML representations both of multimodal coding and of multidimensional annotation of dialogue behaviour, showing how dialogue act annotations can be attached to multimodal data and how dialogue act annotations can be related to XML representations of multimodal functional segments.

In the near future we intend to extend this study in two directions. First, we will apply action recognition software that has recently been developed at Vicomtech, which is based on a robust approach to action unit tracking, segmentation and classification. The output is a sequence of time ordered action units that will be compared with manually
performed codings in order to improve the automatic feature selection and classification. With the help of this new software, we plan to produce a corpus of automatically transcribed and annotated AMI data. Second, with the corpus data obtained in this way we plan to perform experiments in automatic multimodal dialogue act recognition, from which we expect to gain a deeper understanding of the role of nonverbal communicative behaviour in dialogue.

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