A hybrid formalism to parse Sign Languages

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Abstract

Sign Language (SL) linguistic is dependent on the expensive task of annotating. Some automation is already available for low-level information (e.g., body part tracking) and the lexical level has shown significant progresses. The syntactic level lacks annotated corpora as well as complete and consistent models. This article presents a solution for the automatic annotation of SL syntactic elements. It exposes a formalism able to represent both constituency-based and dependency-based models. The first enable the representation the structures one may want to annotate, the second aims at fulfilling the holes of the first. A parser is presented and used to conduct two experiments on the solution. One experiment is on a real corpus, the other is on a synthetic corpus.

1 Introduction

To study Sign Languages (SLs), linguistic needs annotations. Currently, corpus annotation is done manually. It is time-consuming, error prone and non-reproducible. For this reason, efforts are carried out to automatize the annotation process. Early efforts focused on the very low-level: non-linguistic information: body part tracking, activity detection. They finally reached the base of the linguistic level: detection of sign phases (González and Collet, 2011), sub-lexical (Cooper et al., 2012) and lexical units (Curiel and Collet, 2013). Work on this last level has focused on manual gestures. The only exceptions were attempts to remove ambiguity on some lexical signs with the help of Non-Manual Gestures (NMGs) (Paulraj et al., 2008) or detection of NMG (Yang and Lee, 2011) [Neidle et al., 2009]. Now is the time to address the annotation of supra-lexical features, and therefore the necessary NMGs.

The SL syntaxes are complex and different from vocal languages. They use the multiplicity and the spatial abilities of their articulators. It results non-sequential productions with complex temporal, spacial and articulatory synchronizations. Consequently, the processing of SL syntaxes requires to invent new models or, at least, to deeply rethink and adapt the existing ones.

There are multiple manners to obtain the representation of a phenomena needed for its automatic recognition. It can be expert knowledge formalized into a model as well as results of uninformed automatic learning. The first requires experts to formalize a complete and consistent model from their knowledge. The second requires massive data and computer calculus. For the SL syntaxes, neither is available. The expert knowledge is sparse and sometimes inconsistent. Annotated SL corpora are too small and heterogeneous for uninformed learning.

This article exposes elements in favor of a hybrid parsing of SLs. It presents a formalism able to represent constituency-based structures (section 2.1) as well as dependency-based structures (section 2.3). This formalism has been created to represent models combining transferred linguistic knowledge and automatically learned dependencies. We aim at enabling the use of incomplete models transferred from the linguistic knowledge with learned data (section 2.2). The feasibility is demonstrated with a parser (section 3) on two experiments (section 4). First, the parser is run on excerpts of the Dicta-Sign Corpus with a model composed of 5 structures. Second, synthetic dependency grammars are used to parse synthetic corpora.

The present formalism and parser make avoids the assertions of predominance of the hands (on the other articulators) and of existence of a sequential skeleton of the SL locutions. It is based on the ideas introduced by Filhol (Filhol, 2009).
of representing structures with the minimal constraints that make them recognizable. This enables to naturally represent the complex temporal synchronization mechanisms (Filhol, 2012) of the SL simultaneity (Vermeerbergen et al., 2007).

2 Formalism description

The first step toward the automatic annotation is the formal representation of a model. The representation we propose is similar to Context-Free Grammars (CFGs) in that it is a derivational grammar. But it differs from CFGs on three fundamental points. First, the right hand side of a production rule is not a string of units but a set of units. Second, it introduces the possibility to express constraints between all the units of a production rule. Third, in CFGs, the left hand side of a production rule is non-terminal symbol. We have no such thing as non-terminal and terminal symbols. We have instead detectable and non-detectable units, and both can be atomic (terminal) or not.

We target the representation of two types of models. In the first, a production rule represents a relation of constituency (from Chomsky’s Phrase Structure Grammars (PSGs)). In the second, a production rule represents a relation of dependency (from Tesnière’s dependency grammars).

2.1 Constituency structures

2.1.1 Example presentation

We illustrate the description of the formalism with the construction of a constituency-based model from an excerpt of a real corpus.

The excerpt comes from the French Sign Language (LSF) part of the Dicta-Sign corpus (Efthimiou et al., 2010) which is made of spontaneous dialogs performed by deaf signers. In this excerpt, the informant relates a memory of a journey in Paris to visit the Louvre museum with a friend. The figure 1 summarizes the excerpt with a sequence of pictures.

2.1.2 Pattern decomposition

We call pattern a rule representing how a unit comes with others. It is similar to the production rules of CFGs. We usually draw this patterns as trees as shown in figure 2. Pattern identifies to a unit (this inverse is false, it is not an equivalence), this means a unit can be the root of at most one pattern for a given model. An atomic unit is associated to a pattern with only a root. It is the only hypothesis regarding units and patterns in a model. It is therefore possible to have units appearing several times in a pattern. Patterns can also be recursive, mutually recursive, etc.

The model we are about to introduce contains four patterns observed in the excerpt: a buoy pattern, a “sign check” pattern, a question pattern, and an acknowledgment pattern. These patterns are examples and do not rely on a strong linguistic basis. Stronger models remain to be developed with linguists.

The patterns are described in terms of constituents as shown in figure 2. Their internal arrangement is then described with constraints (section 2.1.4).

The first described pattern is a buoy (Liddell, 2003). It is visible on the figure 1, the left hand of the bi-manual sign TO-VISIT (fig. 1(a)) is maintained all along the excerpt. The pattern is decomposed into three sub-elements: two signs and one locution. The second pattern is an acknowledgment. It happens on figure 1 (g). It is decomposed into two sub-elements: a head node and a sign. The third pattern is a question. It also happens on figure 1 (g), but is less clear on this snapshot. It is decomposed as a marker (eyebrows up) and a locution. The “sign check” is a question and an acknowledgment.

As shown in figure 2, the pattern decomposition can be easily represented as a tree. The sub-elements are patterns which can be decomposed themselves or can be considered atomic in the model. Edges represent a relation of constituency. In a decomposition, multiple elements can be instances of a same pattern. When defining a model, one can need to introduce a same pattern multiple times in a same decomposition. This fact is of particular importance as it highlights that an element, in a decomposition, does not represent a pattern but an instance. As a consequence, the name of a pattern is not sufficient to designate an elements without ambiguity. It is therefore necessary to associate each instance with a role name.

2.1.3 Alternatives

Patterns do not allow generalization as all their internal elements are mandatory. As patterns describe compositions, we define another type of rule to explicitly express alternatives. The same restriction as for patterns applies on the use of a unit as root for an alternative. In the example model, we define a node Locution as an alternative
Patterns and alternatives represent invariants in the composition. Invariants in the internal organization of the patterns are expressed with constraints.

To come back to the example, we can extract several kinds of invariants. One may hypothesize that the sign beginning a buoy structure must be bi-manual (figure 2b). Another may want to describe the temporal structure of the patterns (Buoy finishes BuoyStruct, in figure 2b). It could be also useful to express global constraints as the fact the time intervals of sub-elements are always contained in the time interval of the pattern. All these invariants should be expressible formally.

We represent temporal, spatial and articulatory invariants as constraints. The constraints restrain the possible values for the attributes of pattern instances. The attributes, their encoding, and the logic formalisms—used to express the constraints—are a whole. Their choice strongly impacts the model. This is the reason why the formalism has to be independent of the logics and attributes.

Representing a complete model requires multiple logics, each addressing a different aspect: temporal, spatial, articulatory, etc. We showed examples of the temporal (finishes) and articulatory (bi-manual) aspects. In this article, we focus on the formalism to describe the model. For this demonstration, only temporal constraints are used.

2.2 Edges of the models

As developing a complete model is—at best—very hard, we combine two approaches to enable the work on incomplete models. The first is to transfer the charge on the human operator. The second is to use coarse-grained models. Such a model is not meant to produce analyzable results but black-box units. In the example, we have experimented a coarse model, for “unmodeled-loc”, based on the sequence of lexical signs. It gave bad results. We expect to build better coarse-grained models with dependency grammars.

2.3 Dependency structures

For the dependency grammar part, we present the formalism with a simplified model. The units can represent as well standard signs, other Manual Gestures (MGs) (e.g. pointing MGs), facial gestures (e.g. qualifiers, quantifiers, modality markers), gaze gestures (e.g. references), etc. But we simplify the complex articulatory constraints resulting by dividing the units in two types: MGs and NMGs. MGs never overlap, and all NMGs can overlap freely. The first is a simplification as it excludes the representation of yet described phenomenons (e.g. buoy structures, Cuxac’s situational-transfers (Cuxac, 2000)). The second is a simplification as some NMGs are articulatory impossible to produce simultaneously. This model enable the use of a slightly extended version of the Hays’ formalism. Indeed, this formalism is sufficient to represent MGs, but the NMGs requires a supplementary type of rule of the form $X(Y)$. We have represented such dependency structures with a construction shown in figure 3. The cate-
gories are described as alternatives between rules, and the rules as patterns. The constraints remain exactly the same.

3 Parsing

The presented formalism is used to describe models for recognition. The recognition itself has been implemented in a parser. We give here an outline only of the developed system. The detailed description is the subject of a dedicated article.

In addition to the formalized model, the parser needs an input to parse. This input is an annotation of a subset of model’s units (as well pattern as alternatives). Units of this subset are said to be detectable. Their annotation can originate from manual annotation or third party detectors. Detectable units appear in red on the figures. The parser is able to work interactively with the detectors. In this case, it informs the detectors of the context and therefore reduces their search spaces.

Our work extends the ideas of Mahanti (Mahanti et al., 2003) for the parsing. The internal representation of the model in the parser is an AND/OR graph. This representation is called the implicit graph. In this nodes represent units and not instances. The figure 4 gives an example of graph. The parser then explore an explicit graph (without building it) to find subgraph which are solutions. The figure 5 shows an example of such solution as output by the parser. The nodes represent occurrences either externally detected or internally inferred. The arcs correspond to constituency or dependency relations of the model.

The parser is currently top-down. It builds the solution graphs starting from a set of given roots. This set can be, for example, a set of pre-detected lexical unit occurrences resulting of a first pass of lexical recognition. It is how the parser process dependency-based models. It, then, builds trees top-down from each root and merges the trees when possible. It is therefore obvious than solution graphs can have multiple connected components. This appears, for example, when a signer is interrupted by a question, answers quickly and then continues his/her speech. In the case of constituency-based models, the top-down parsing requires to introduce a detectable root. It is the function of the “Signing” unit in figure 4 which is detected with an activity detector.

4 Results

The parser has been evaluated for constituency-based and dependency-based structures: the first on real annotations, the second on synthetic data. When evaluating on constituency-based structures, the external detectors were simulated with a manual annotation of the detectable units. We lacked annotations to produce a quantitative evaluation. But qualitatively, the parser outputs too much solutions: partial solutions and false-positives. A simple ranking is efficient against the partial solutions. We split the false-positives in two categories: wrong hierarchical order and bad modeling (as discussed in section 2.2). The first could be addressed with recursive constraints on the compositions (for example, “the locution constituting a question cannot contain a question”). Such a feature could be interesting for experimentations on models, but in a context of semi-automatic annotation, we rather think that this type of false-positives must be resolved by a human expert. Such a system is still of good help, it reduces the work to the task of selecting the right hierarchical organization. This uses the expertise of the operator for high-level problems. The second type of false-positives comes from the difficulty we met to model the syntactic structures of low-level. It is the reason why we developed the dependency part of our formalism.

The parser is evaluated for dependency grammars on a synthetic corpus. The synthesis uses the model presented in the section 2.3. It is random phrases built with random grammars. By lack of measures on annotations, the model has been parametrized arbitrarily. The corpus has 5000 grammars with 1 phrase each. All grammars have 20 categories. Every category has 3 to 4 rules each. For manual categories, sizes have a uniform distribution on $[0, 4]$. The results of the parsing on the synthetic corpus are visible on the figure 6. We have an average of 1 to 4 false-positives per phrase. It gives a precision of 52% to 5%. The recall of 83% to 23% is much more interesting for a semi-automatic system. It is hard to guess
how these results will extend to real corpus. It, at least, validates the computability of the parsing including with the proposed representation for dependency structures.

5 Conclusion

The formalism of this article showed its ability to represent structures based on constituency as well as dependency relations. It has been done without hypotheses on the sequentiality of lexical units neither on the predominance of the manual gestures. Instead, it uses constraints to describe invariants on the composition of the structures and on their temporal organization. We showed that these descriptions allow the detection of the structures. We gave elements showing the interest to combine the two paradigms to avoid the use of mis-constructed low-level structures. However, the articulation between the two paradigms in one model remains to be experimented. For now, the solution is to have two separated models. The dependency-based model is used when a non-modeled pattern is reached. At this time, the human operator decides if the pattern is present and which solution of the dependency parsing will act as the occurrence of the non-modeled pattern.

This work, in its current state, suffers some limits of the generative grammars. But it already avoids the problem of designing a model with an unique root for dependency grammars. This is critical in our context of semi-automatic annotation, as our goal is to enable the detection of structure occurrences, not to produce an interpretable syntactic tree. Unfortunately, the parser is still top-down, and consequently, the constituency-based grammars still need a root. There are plans to modify the current parser to drop the top-down mechanism. This will enable the parser to accept non-rooted models.

To go further in the direction of the automatic annotation, several points need to be worked on. First, one will have to build (manually or automatically) a dependency grammar compliant with a real SL. The formalism and the parser can manage models of dependency grammars much more complex than one presented above.

The formalism and the parser do not represent uncertainty. But there are good candidates to in-
roduce uncertainty representation in the existing parser such as fuzzy-CSPs. This extension will certainly improve greatly the results but will also have a computational cost.

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