Challenges in Development of the American Sign Language Lexicon Video Dataset (ASLLVD) Corpus

Carol Neidle*, Ashwin Thangali, Stan Sclaroff****
Boston University
*Linguistics Program, 621 Commonwealth Ave.; **Computer Science Department, 111 Cummington St.
Boston University, Boston, MA 02215
E-mail: carol@bu.edu, tvashwin@cs.bu.edu, sclaroff@bu.edu

Abstract

The American Sign Language Lexicon Video Dataset (ASLLVD) consists of videos of >3,300 ASL signs in citation form, each produced by 1-6 native ASL signers, for a total of almost 9,800 tokens. This dataset, including multiple synchronized videos showing the signing from different angles, will be shared publicly once the linguistic annotations and verifications are complete. Linguistic annotations include gloss labels, sign start and end time codes, start and end handshape labels for both hands, morphological and articulatory classifications of sign type. For compound signs, the dataset includes annotations for each morpheme. To facilitate computer vision-based sign language recognition, the dataset also includes numeric ID labels for sign variants, video sequences in uncompressed-raw format, camera calibration sequences, and software for skin region extraction. We discuss here some of the challenges involved in the linguistic annotations and categorizations. We also report an example computer vision application that leverages the ASLLVD: the formulation employs a HandShapes Bayesian Network (HSBN), which models the transition probabilities between start and end handshapes in monomorphemic lexical signs. Further details and statistics for the ASLLVD dataset, as well as information about annotation conventions, are available from http://www.bu.edu/asllrp/lexicon.

Keywords: American Sign Language, lexicon, computer-based handshape recognition

1. Introduction

The American Sign Language Lexicon Video Dataset (ASLLVD) arose from collaboration among computer scientists and linguists to develop sign lookup technology (Athitsos et al., 2010). Several multimedia resources for ASL are under development, but available interfaces for sign lookup remain less than optimal. The ideal interface would enable users to search the dataset simply by video-recording a sign and relying on computer-based sign recognition for lookup.

To train computer algorithms to distinguish and recognize ASL signs, we created a corpus with ~3,000 signs from up to six native signers. Our sign recognition and retrieval algorithms rely in part on linguistic models. Initial research has focused on the benefits for robust sign recognition of exploiting constraints on the relationship, in monomorphemic lexical signs, between start and end handshapes (and between the two hands, in two-handed signs) (Thangali et al., 2011).

Linguistic annotations have been carried out to facilitate this research. Specifically, we assigned each sign a unique gloss label; identified variants of specific lexical items; and labeled start/end handshapes. This corpus will be shared publicly once verifications are complete. It will also be integrated with another corpus that we already make available for online browsing and download: our National Center for Sign Language and Gesture Resources (NCSLGR) corpus, which can be accessed from http://www.bu.edu/asllrp/ (see Neidle & Vogler (2012)). Through extensions to our web interface, it will be possible to search our lexical and continuous signing data in various ways, and to go back and forth between different data types, e.g., between viewing a sign in citation form or produced in a natural context.

For verifying these large data samples—to enforce consistency in labeling and in groupings of sign variants—we have developed a powerful tool: the Lexicon Viewer and Verification Tool (LVVT). We will (a) describe the data collection, (b) discuss challenges for elicitation, consistent annotation, and classification of data, (c) present a brief overview of the data that we have amassed and statistics thereof, (d) describe a computer science research project that leverages the detailed annotations of the ASLLVD dataset, and (e) outline directions for future research.

2. Data collection

Videos were captured using four synchronized cameras. Thus for each sign production, we have a side view of the signer, a close-up of the head region, a half-speed high resolution front view, and a full resolution front view.

The consultants, ASL native signers, were shown video prompts (from the *Gallaudet Dictionary of American Sign Language* (Valli, 2002)) and asked to reproduce the signs as they naturally would (or not, if they do not use that sign). Signers did not always produce the same sign shown in the prompt. In cases where a signer recognized and understood that sign but used a different sign or a different version of the same sign, divergences showed up in the data set. So, in reality, a given stimulus resulted in productions that may have varied in any of several different ways: production of a totally different but synonymous sign; production of a lexical variant of the same sign; production of essentially the same sign but differing in subtle ways with respect to the articulation.

As displayed in Figure 1, we collected a total of 3,314 distinct signs, including variants (for a total of 9,794 tokens). Among those were 2,793 monomorphemic lexical signs (8,585 tokens) and 749 tokens of compounds, which

Class of signs	Number of signs	Number of sign variants	# sign variants with { 1, 2, 3, 4… } consultants		# tokens (examples) per sign { 1,2,…,6, >6 }		Number of sign tokens	
Monomorphemic lexical signs	2,284	2,793	x1	621	587	x1	8,585	Two-handed
			x2	989	858	x2		5,713
			x3	394	386	x3		67%
			x4	563	491	x4		
			x5	85	142	x5		One -handed
			x6	141	154	x6		2,873
					175	>6		33%
Compound signs	289	329	x1	129	117	x1	749	
			x2	106	107	x2		
			x3	48	46	x3		
			x4	33	33	x4		
			x5	4	11	x5		
			x6	9	13	x6		
					2	>6		
Number signs	76	88					260	
Loan signs	46	52					136	
Classifier constructions	27	31					38	
Fingerspelled signs	21	21					25	
ALL	2,742	3,314	--	--	--	--	9,794	

Figure 1. Overview of statistics from the dataset

provide fertile ground for studying assimilation effects. Column 4 shows the total number of sign variants we have as produced by 1 signer, 2 signers, etc. Since in some cases we had more than one example per signer, the total number of tokens per sign was, in some cases, greater than 6.

3. Resources to be made available

Linguistic annotations are in the final stages. Once this has been completed, the video files and associated annotations will be made publicly available. Details about this will be provided on our website when the materials are ready for release (http://www.bu.edu/asllrp/lexicon).

3.1. Video data

Video sequences will be made available in uncompressed-raw format, along with camera calibration sequences and software for skin region extraction. Hand location bounding box coordinates (either in each video frame or only for the start and end frames of a sign) will be accessible for a subset of signs in the dataset.

3.2. Linguistic annotations

Linguistic annotations, carried out using SignStream®3 (beta), will also be made available in XML format. These include gloss labels and start/end time codes for each sign, labels for start and end handshapes of both hands, morphological classifications of sign type (lexical, number, fingerspelled, loan, classifier, compound), and articulatory classifications (1- vs. 2-handed, same/different handshapes on the 2 hands, same/different handshapes for sign start and end on each hand, etc.). For compound signs, the dataset includes annotations as above for each morpheme. To facilitate computer vision based sign language recognition, the dataset also includes numeric ID labels for variants of a sign.

4. Challenges faced for linguistic annotation and categorization of signs

This data set will serve as the basis for development of sign lookup technology. That is, we ultimately want to be able to identify automatically, from a video, the identity of the sign that was produced, so that this can serve as an entryway for lookup in an ASL dictionary. Some of the decisions with respect to annotation were made with this kind of application in mind. For example, for such research, it is essential that there be a 1-1 correspondence between sign and label. The American Sign Language Linguistic Research Project (ASLLRP) based at Boston University has been using unique gloss-based ID labels throughout the development of all of our corpora — including our NCSLGR corpus — since the early 1990's.[1] Although our annotation conventions (Neidle, 2002, 2007) have evolved slightly to deal with issues that have

[1] For further discussion of ID-glosses, in particular, and the types of issues that arise in the annotation of signed language corpora, see Johnston (2010).

arisen as the corpus has expanded (a 2012 version documenting recent modifications is currently in preparation), the essential goal with respect to the gloss-based labeling of signs has remained constant:

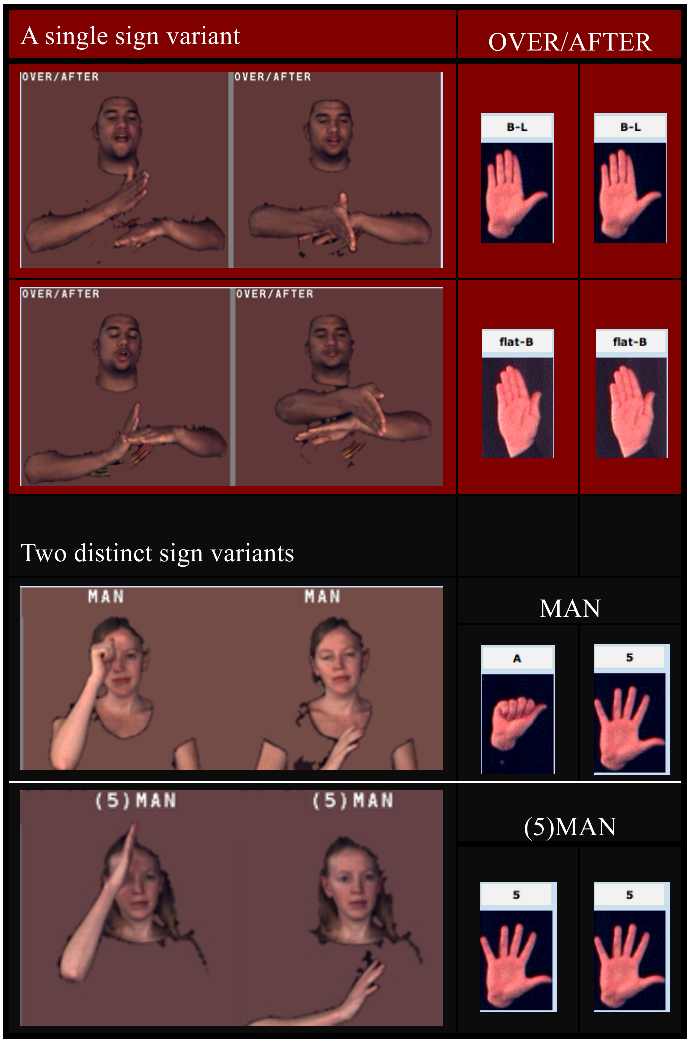
> To facilitate both linguistics and computer science research, we have tried our best to settle on conventions to ensure that every time a particular English gloss is used, it corresponds to a unique ASL sign, and conversely, that the same ASL sign will have a predictable English gloss. (Neidle, 2007: p. 3)

There were challenges in ensuring consistency across annotators, and in assigning unique gloss labels while also enforcing consistency with glossing conventions for our other corpus. There were also challenges involved in assigning consistent handshape labels to hand configurations that sometimes did not exactly match any of our 86 canonical handshapes (we included an 87th that we labeled as a "relaxed handshape" and an "other" option when the handshape used failed to correspond with any of the other handshapes):

http://www.bu.edu/asllrp/cslgr/pages/handshape-palette.html

For handshapes that fell in between two of our existing handshapes, the danger is that what might appear, from the annotations, to be variations in production might, in fact, turn out to be merely inconsistencies in how the same handshape had been annotated. To some extent, this is unavoidable given the gradient nature of some of the handshape productions, but the ability to view exemplars of a given sign together, and to search for handshape annotations across the dataset, makes it considerably easier to do side-by-side comparisons and to increase the degree of consistency in the annotations.

We encountered various thorny issues in assessing variation: When should two productions be considered distinct signs, variants of the same sign, or the same variant of a single sign? In principle, we did not separate out as variants productions differing solely with respect to general ASL linguistic processes (not specific to the particular lexical item). For example, productions that differed in an alternation between a flat-B and B-L handshape (e.g., for the dominant hand of OVER/AFTER) were considered to be instantiations of the same sign variant, since there is, in general, widespread variation between these two handshapes, not restricted to this particular sign. In fact, there are 157 forms where variation between these two handshapes was attested. There are other cases, however, where the manifestation of two different handshapes is tightly linked to the particular sign, an example being the alternation between the A and 5 start handshape in MAN (or WOMAN). This kind of alternation is not widespread and is restricted to a small set of lexical items. Thus, MAN and (5)MAN have been distinguished in glossing and classified as two variants of the same sign. These examples are illustrated in Figure 2.



Start and end frames | Start /end dominant handshapes

Figure 2. Predictable variation in handshapes [B-L/flat-B] vs. lexically dependent variation [A/5]

However, the status of handshape variations was not always clear, particularly because we often had only one or few tokens of each sign per signer, so issues of inter- vs. intra- signer variations were sometimes difficult to tease apart at the time annotations were initially conducted. Such issues are quite interesting, though, and become more tractable when we can examine patterns across the entire dataset and probe further with signers about the equivalency or non-equivalency in their own signing of specific handshape variations for a given sign. Given the intended application (computer-based sign lookup), we focused on the way the signs were produced. In the case of homonyms, we used the same gloss for all, despite the fact that it was often impossible in the labeling to account for the full range of meanings. We expect that the eventual dictionary lookup will provide access to the various distinct meanings that can be associated with a given production. However, here again, there were some difficult cases, where some but not all realizations of two given signs were distinguishable from one another. For example, we classified CHEW and WASH in Figure 3 as distinct signs, even though in many cases, it would be hard to distinguish productions of the two. [2]

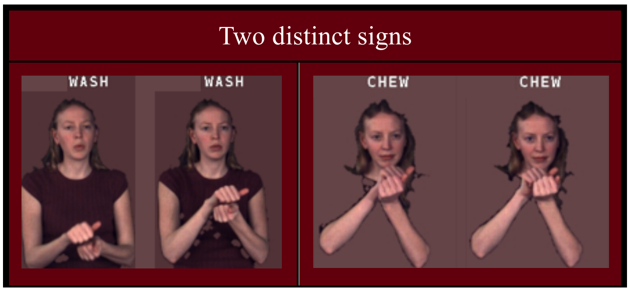


Figure 3. WASH vs. CHEW

In such cases where there is some degree of similarity that may be relevant for an eventual lexical lookup process, we have grouped the lexical items together, but we consider them to be linguistically distinct.

We generally did not separate out signs for which production differed only in the number of repetitions or reduplications of the base form, even though this frequently (but not always) results in a difference in meaning. We indicated the number of repetitions through the use of the + symbol, but considered the productions that differed in this way to be instantiations of the same sign variant. In cases where the productions with and without reduplication differ in meaning, disambiguation would need to occur at the dictionary lookup stage.

The challenges that we have faced with annotation and categorization of signs—which are far too numerous and varied to list exhaustively in the present context—are not unique to this project. The same kinds of issues necessarily face other sign lexicon projects. For that reason, we believe that the kind of tool discussed in the next section has the potential to facilitate such efforts and increase the accuracy of annotations and classifications.

5. Tool for browsing and verification

The Lexicon Viewer and Verification Tool (LVVT) was conceived and developed to aid in viewing, comparing, verifying, and modifying SignStream® annotations. The LVVT is designed to assist the annotator in the daunting task of ensuring consistency of the labeling of glosses and articulatory attributes across several thousand tokens.

In developing the LVVT we drew inspiration from the search and browsing functionality implemented in the ASLLRP Data Access Interface (DAI) (Neidle & Vogler, 2012). The LVVT extends the DAI's feature set by enabling users not only to browse the data, but also to modify displayed attributes for signs. Presently, the attributes supported are the gloss labels, start/end handshapes, start/end timecodes in video, and the morphological and articulatory classifications of signs. In addition to presenting an interface for the annotator to search, browse, compare and modify annotations for signs, we believe an important contribution of the LVVT is in facilitating groupings of signs to be constructed.

We define a two-level grouping layout for signs in the lexicon dataset so as to clearly distinguish cases where we have distinct *signs* from those in which we are dealing with *sign variants*.

(1) Occurrences of a given sign may be subdivided into several distinct variants. Occurrences classified as belonging to a single *sign variant* are deemed to differ from one another only as a result of general language processes that are not sign-specific. As mentioned in Section 4, we do group together signs that differ in the presence or absence of reduplication (indicated by '+'); thus all examples considered to be instantiations of a single variant may not be identical in meaning. A sign with four variants is illustrated in Figure 4 (bottom): ABORTION_2 differs from ABORTION in the orientation of the non-dominant hand, (1h)ABORTION is a one-handed sign and, (S)ABORTION uses a different start handshape on the dominant hand.

(2) Loosely related (but distinct) signs can be further organized by means of higher-level groupings. This is intended solely to aid in navigating the dataset. These groupings are for our convenience in working with the data and have no linguistic significance.

Each grouping of signs and sign variants is annotated with a unique gloss label, and with a pair of numeric IDs to denote its location in the upper and lower levels of the two-level grouping layout.

The general listing of signs in the sign index is shown in the left column of Figure 4 (top). The higher-level groupings are visible from the presence (or absence) of a ♦ (diamond) prefix, which indicates that a contiguous sequence of gloss labels belong to the same sign collection, e.g., HOW-MANY and (1h)HOW-MANY are in one high-level grouping; HUMBLE, (H)HUMBLE, and (1)HUMBLE are in another. In both of those cases, those groupings contain a single sign with more than one variant. Note also, however, that HUSBAND (a monomorphemic sign) and the closely related compound BOY+MARRY (from which HUSBAND evolved), are also grouped together, albeit as distinct signs.

The LVVT has proven to be very useful for comparing similar forms, for ensuring consistency of annotations, and for determining how they should best be categorized in relation to one another. Of particular benefit is the ability to view still images of the start and end frames together across the range of sign tokens, and to play the video files from two different camera views of multiple signers producing the same sign simultaneously. Figure 5 depicts a snapshot of a video sequence presented to the annotator for the purpose of verifying consistency in the grouping. By viewing the data in these ways, we can discover sign variants that had not previously been noticed as distinct by the annotators, and conversely can discern similarities in production of signs that previously may have been categorized as distinct.

[2] According to Vicars (2012), "the movement of 'wash' is two steady circles. The movement of 'chew' is [very slightly] more elliptical and uses a bit (but not much) more shoulder/elbow movement as the hand circles toward the body."

Through use of the LVVT, corrections to glosses, start/end frames, handshapes, and/or classifications and groupings of signs can also be carried out directly, in a simple, intuitive way, e.g., by clicking on a handshape icon associated with a sign to bring up the handshape palette, then clicking to select a replacement for an erroneous handshape. The user interface elements for annotating the gloss and other attributes for each sign are displayed in the last column in Figure 4 (top).

Various corpus properties can also be displayed, and many different types of searches can be performed. For example, Figure 6 shows part of a chart illustrating, for monomorphemic signs, the most likely end handshape given a particular start handshape. The particular start and end handshape combinations can (with a single mouse click) be entered into a search box in the LVVT, and all relevant examples will be listed. Search queries can be carried out for particular handshapes (start and/or end of dominant and/or non-dominant hands), potentially in combination with a variety of morpho-phonological properties and categorizations.

The LVVT also includes an interface for working with compound forms. The LVVT presents the annotator with the same set of features for annotating morphemes in

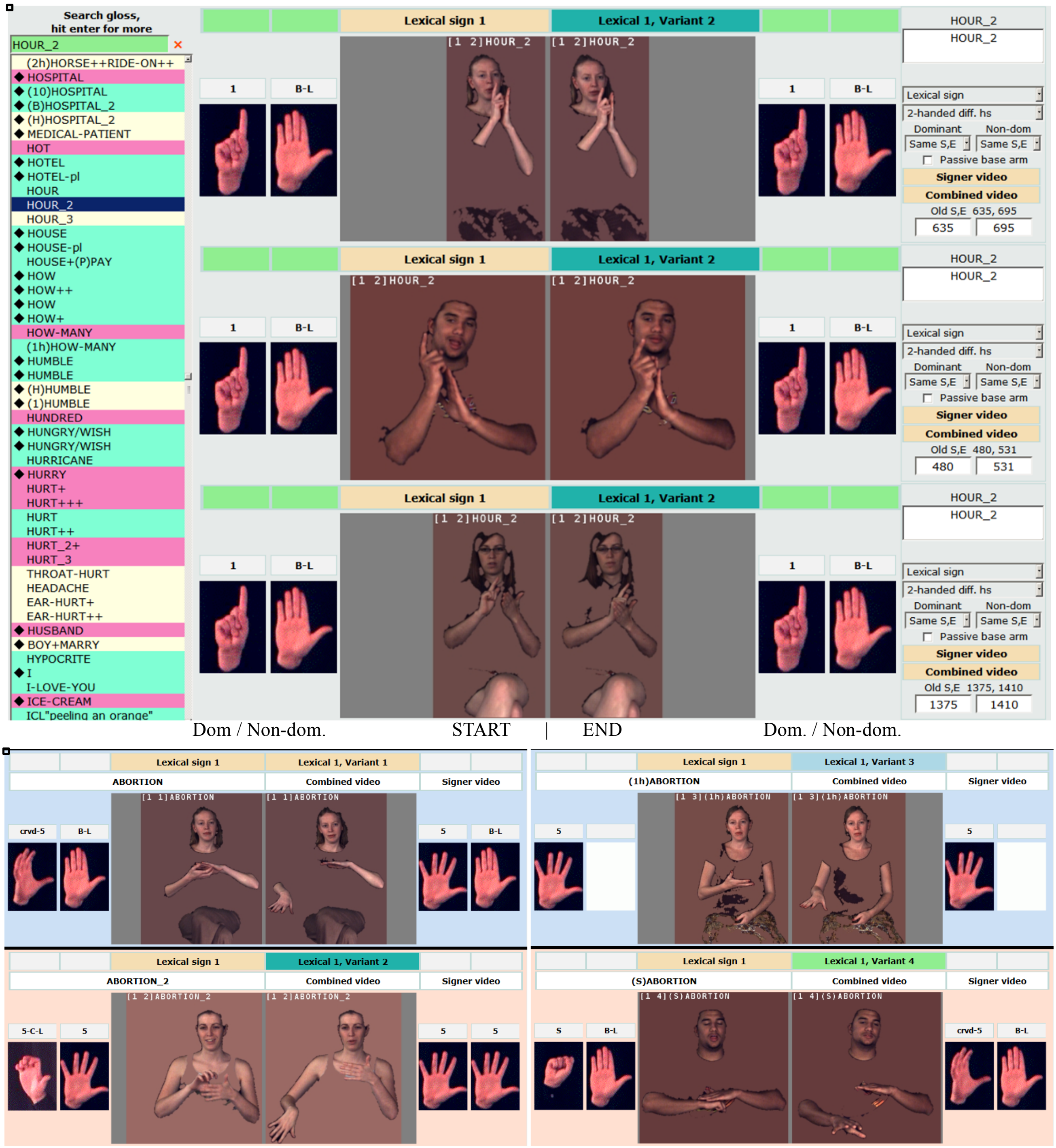


Figure 4. Lexicon Viewer & Verification Tool (LVVT): main page with listing of signs (top) and display of sign variants (bottom)

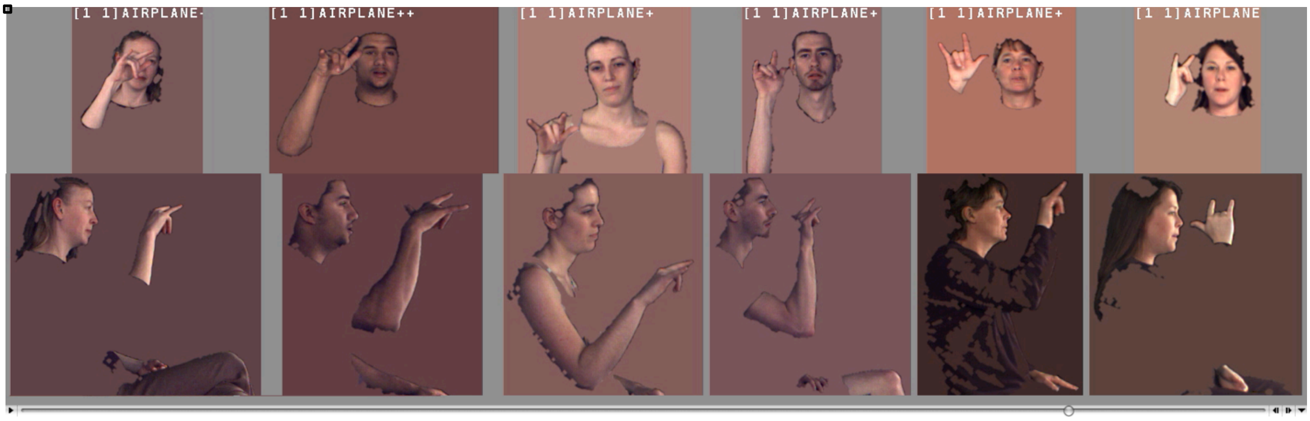


Figure 5. The LVVT enables combined videos (front and side views) to play simultaneously

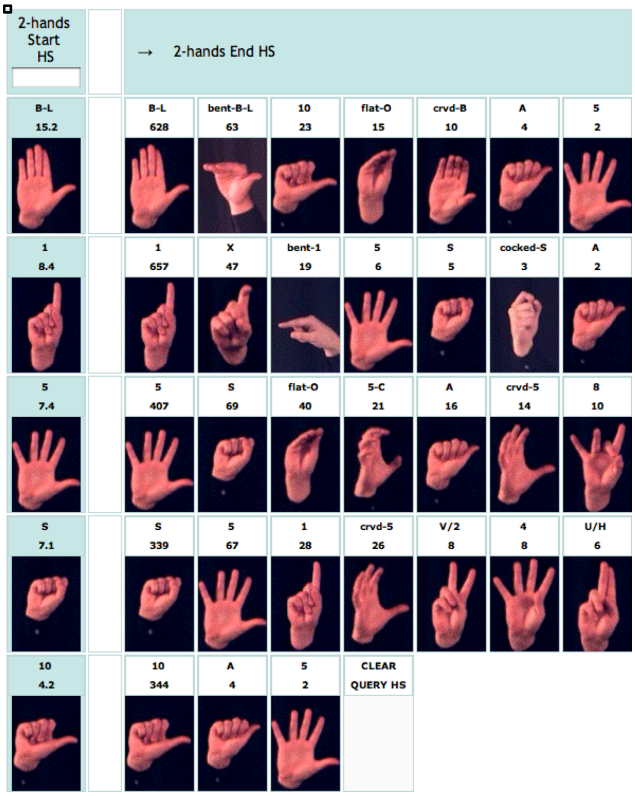


Figure 6. Excerpt of chart showing likely end handshape given the start handshape on the left; shown in order of decreasing frequency

compound signs as are available for monomorphemic signs. This interface makes it simple to view all compounds that share a particular morpheme, for example. The morphemes in compound signs can also be compared to their non-compound versions to ascertain consistencies in glossing and other annotated attributes.

6. Computer science research

One important goal of the ASLLVD is to support development and evaluation of algorithms that can distinguish and recognize ASL signs. As an example application, we have developed a computer vision approach for handshape inference that utilizes a HandShapes Bayesian Network (HSBN) (Thangali, et al. 2011), which models the transition probabilities between start and end handshapes in monomorphemic lexical signs (i.e., simple signs).

A challenging aspect of handshape identification by computer from video is the fact that 3D hand configurations are visible only as 2D images. We demonstrate that the HSBN is able to help in the handshape recognition problem by exploiting general properties for how handshapes are sequenced and how their variations are realized in simple signs. While many previous approaches (e.g., Bowden et al., 2004; Liwicki & Everingham, 2009; Vogler & Metaxas, 2004) have trained Hidden Markov Models (HMMs) that are specific for each sign/utterance to be recognized, the HSBN represents phonological properties that are applicable to all simple signs. The HSBN parameters are automatically learned from the linguistic annotations of signs in the ASLLVD dataset.

The annotations for each sign in the ASLLVD that are used in training the HSBN include: the handshape numeric ID for the start and end handshapes on each hand, the bounding box coordinates of each hand in the start and end frames, and a classification denoting each sign as either one-handed, two-handed:different handshapes, or two-handed:same handshapes. The HSBN training algorithm also exploits the property that the signs in the dataset are grouped into variants (as in Figure 8). Since the variations in handshape within each group are produced as a result of general language processes that are not specific to a particular sign, the HSBN representation is able to model such variations.

Figure 7 illustrates the HSBN graphical models for the three main articulatory classes. Each node in the graphical model represents a variable in the HSBN. Each HSBN comprises three layers. The lowest layer represents the actual image observations provided to the model; these are the cropped images of each hand at the start and end of the sign. The nodes in this layer are shaded to indicate that they are observed (given) during training and inference. The middle layer in the HSBN represents the IDs of the realized handshapes on each hand. Nodes in the middle layer are partially shaded to denote that annotations for handshape IDs are available in the training set, but the IDs must be inferred (i.e., they are not given) when the trained HSBN is used for recognizing

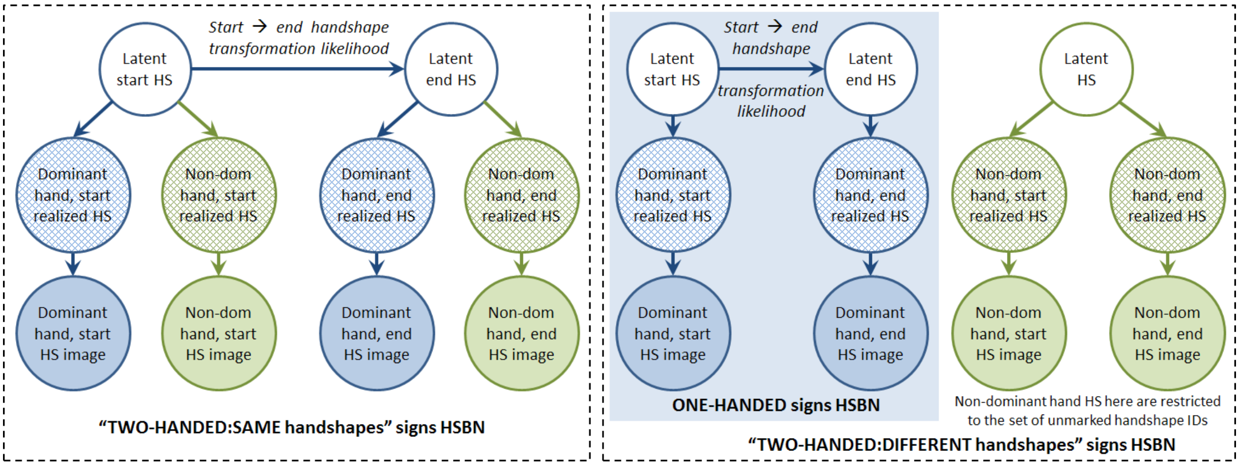


Figure 7. The model on the left represents the HSBN for two-handed:same handshapes signs. The model shown inset on the right represents the HSBN for one-handed signs. In two-handed:different handshapes signs, the HSBN for handshapes on the dominant hand is the same as that of one-handed signs; handshapes on the non-dominant hand are, however, limited to a small number of unmarked handshapes and hence are represented using a separate HSBN.

handshapes in signs. The top layer of the HSBN is a "latent variable" layer that represents the unknown, underlying start and end handshapes (since only realized handshapes are known in training, we model the underlying handshape as a hidden layer in the HSBN whose representation is learned during model training).

The arrows in the graphical models (Figure 7) denote different conditional probability distributions in the HSBN. The horizontal arrow in the top layer represents dependency of the end handshapes on the start handshape, i.e., the likelihood that certain hand configurations appear as end handshapes among simple signs that use a specific start handshape. The arrows connecting the top layer and the middle layer serve two purposes: (a) they represent handshape variability, wherein closely related handshapes may be variant realizations of a hypothetical underlying handshape, and (b) the two pairs of arrows in two-handed-same signs represent bilateral symmetry in the start/end handshapes. The arrows between the middle layer and the lowest HSBN layer represent the relationship between the handshapes that are produced by the signer and their observed images.

Handshapes of the dominant hand in all three sign classes, and handshapes of the non-dominant hand in two-handed:same handshape signs, share the same phonological properties with regard to start/end handshape transition and handshape variation. The HSBN is thus learned using handshape annotations for signs from all classes excluding handshapes on the non-dominant hand in two-handed:different handshape signs. An auxiliary HSBN to model the latter category is much simpler because the handshapes on the non-dominant hand are restricted to a small set of unmarked handshapes without change in handshape between the start and end points of the sign.

The formulation has been evaluated in the task of handshape classification using training and test data taken from the ASLLVD. Handshape recognition accuracy is evaluated on a sequestered test set consisting of 1962 {start, end} handshape image pairs obtained from 657 signs (333 one-handed / two-handed:different handshape and 324 two-handed:same handshapes signs). The remaining 6862 simple signs in the ASLLVD are used in the training. As a baseline handshape recognition method, we use an algorithm to assess similarity in appearance among pairs of handshape images (Thangali et al., 2011). Handshape images of the test signer are excluded from the database used for handshape retrieval. Its rank-1 recognition accuracy is 30.4% (597 of 1962). The proposed HSBN exploits information about handshape candidates retrieved for all {start, end} handshape pairs in the query and thus returns a more coherent collection of inferred handshapes. Performing this inference improves rank-1 recognition accuracy to 44.4% (871 of 1692). We believe that this demonstrates the promise of incorporating linguistic constraints in our recognition system, and the training data from the annotated corpus makes learning such models possible.

7. Future aspirations

Once verifications are complete, this set of >3,000 signs, annotated within SignStream®, will be turned into a "sign bank," so that annotators can take advantage of the stored phonological information (which can be further modified) to make the annotation process considerably more accurate and efficient. The annotator will be able to select from available signs and sign variants, and add additional signs or sign variants to the repertoire.

The lexicon corpus data will be released in various forms, including a spreadsheet showing the range of handshape variations for each of the signs in the dataset. For illustration, see Figure 8. This display makes it easy to scan visually for variations in handshapes, for example. As shown in this small sample, the A, S, and 10 handshapes frequently occur in alternation within a single sign variant (despite the fact that they are contrastive for certain signs).

Future plans include integration of the lexicon data with our other datasets, through the Data Access Interface (DAI) that we have been developing, initially to provide

Main Gloss	Consultant	Main Gloss	Variant	D Start HS	N-D Start HS	D End HS	N-D End HS
ACCIDENT	=============	=============	=============	=============	=============	=============	=============
	1	ACCIDENT	ACCIDENT	S	S	S	S
	2	ACCIDENT	ACCIDENT	S	S	S	S
	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	1	ACCIDENT	(5)ACCIDENT	5	5	A	A
	2	ACCIDENT	(5)ACCIDENT	5	5	10	10
	3	ACCIDENT	(5)ACCIDENT	5	5	S	S
	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	4	ACCIDENT	(3)ACCIDENT	3	3	A	A

Figure 8. Excerpt from the summary spreadsheet showing the variants produced by each of the consultants

access to our NCSLGR corpus (of continuous signing: sentences and short narratives), as described by Neidle & Vogler (2012). The interface will be designed to enable searching through the corpora separately, using appropriate tools for each, as well as going back and forth between display of lexical citation forms and of signs in context. Thus, this will require enhancement of our web interface to facilitate searching, browsing and downloading the kind of data and annotations that are contained in the ASLLVD. Ultimately, the plan is to incorporate many of the search functionalities of the LVVT into our main web interface, the DAI.

The LVVT in its current implementation employs signs in citation form. However, we envision that future versions of this system might also collate signs from continuous signing corpora (such as our NCSLGR corpus) where start/end annotations for individual signs are available. This extension could provide a seamless interface for viewing and synchronizing linguistic annotations across what are presently disparate datasets.

Finally, we are pursuing development of a lookup tool to facilitate access to multimedia materials such as ASL dictionaries. Modifications of interfaces we have developed for working with this kind of data (e.g., within the Java reimplementation of SignStream®, where tools are provided to facilitate intuitive data entry of phonological and morphological information) could also allow users to specify partial information about articulatory properties in order to improve upon results of computer-based search and retrieval.

8. Acknowledgments

We are grateful to Vassilis Athitsos, Joan Nash, Donna Riggle, Jessica Scott, Ben Bahan, Rachel Benedict, Naomi Berlove, Elizabeth Cassidy, Lana Cook, Jaimee DiMarco, Danny Ferro, Alix Kraminitz, Indya Oliver, Caelan Pacelli, Braden Painter, Chrisann Papera, Tyler Richard, Tory Sampson, Dana Schlang, Jon Suen, and Iryna Zhuravlova for invaluable assistance with this project. The work reported here has been supported in part by grants from the National Science Foundation (IIS-0705749, CNS-0855065, IIS-0964385).

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