English2BSL: A Rule-Based System for Translating English into British Sign Language

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Abstract

British Sign Language (BSL) is a complex language with its own vocabulary and grammatical structure, separate from English. Despite its long-standing and widespread use by Deaf communities within the UK, thus far, there have been no effective tools for translating written English into BSL. This overt lack of available resources made learning the language highly inaccessible for most people, exacerbating the communication barrier between hearing and Deaf individuals. This paper introduces a rulebased translation system, designed with the ambitious aim of creating the first web application that is not only able to translate sentences in written English into a BSL video output, but can also serve as a learning aid to empower the development of BSL proficiency.

1 Introduction

British Sign Language (BSL) is a visual-gestural language that has been widely used by Deaf¹ communities within the UK for hundreds of years. Contrary to a common misconception, BSL is not merely a visual representation of English; it developed independently of the spoken language, resulting in its distinct vocabulary and grammatical structure. This is evidenced by the fact that despite both BSL and American Sign Language (ASL) emerging in English-speaking countries, the two sign languages are mutually unintelligible, i.e., they share neither a grammar nor a lexicon (Emmorey, 2001).

The British Deaf Association (2023) states that there are more than 87,000 Deaf people in the UK whose first language is BSL. However, a significant lack of hearing people choosing to learn BSL has led to Deaf communities experiencing considerable levels of social exclusion (Berry, 2017), exacerbated by "educational segregation" and a lack of access to health services and employment opportunities (Powers, 2002). Research suggests that integrating BSL lessons and Deaf awareness education into UK schools is highly beneficial, not only for Deaf students but also for their hearing peers (Daniels, 2001). This poses the question: *how can learning BSL be made more accessible?*

Modern technology has provided access to applications that can translate between numerous spoken languages in real-time. Google Translate² can instantly convert written English into over 100 different spoken languages from any smartphone or web browser. As well as being a convenient way to quickly facilitate communication between people who speak different languages, translation applications can also be used as a learning tool. Medvedev (2016) discussed the use of Google Translate as a meaningful resource for learning English. However, there is no comparable application for translating written English into BSL. This gap forms the core motivation behind the development of the English-to-BSL translation system presented in this paper.

Our main contribution is the development of a translation pipeline that is comprised of a bespoke set of syntax-based rules created without the use of pre-existing templates. This unique rule-based translation system enables a user to input a sentence in written English and play a video showing the generated BSL translation. The translation output, which follows BSL grammar, is comprised of a series of sign videos, each representing a BSL gloss.³ Our systematic evaluation of the system

¹The term Deaf with a capital 'D' refers to people who identify as culturally Deaf, i.e., are part of the Deaf community and actively use sign language. The term deaf with a lowercase 'd' refers to the medical definition of having very little to no functional hearing (O'Neil, 2003).

²https://translate.google.com/intl/ en-GB/about/languages/

³A *gloss* is an English-based translation that is consistently used to represent a unique sign (Cormier et al., 2017).

demonstrated the success of the web application from both quantitative and qualitative perspectives.

2 Related work

Below, we provide a summary of previously proposed methods for translating written text to sign language. This is then followed by a review of tools for English-to-BSL translation.

2.1 Methods for Translating to Sign Language

Statistical Machine Translation (SMT) approaches have provided significant advancements in the field of spoken language translation. However, in order to generate high-quality results, a vast amount of data is required to train statistical models. Bungeroth and Ney (2004) proposed a proof-ofconcept SMT model for translating written German into German sign language (DGS). However, their model obtained low performance due to a lack of available German-to-DGS data.

In a recent survey of sign language machine translation, Núñez-Marcos et al. (2022) recognised the overt scarcity of data available for *all* sign languages, which has led to a lack of effective SMT models for translating written text into sign language. BSL is even more under-resourced than DGS in terms of data currently available, therefore developing an accurate SMT approach to English-to-BSL translation is currently not feasible. For this reason, our own English-to-BSL translation tool is underpinned by a rule-based approach that we developed (as described in Section 4).

2.2 English-to-BSL Translation Tools

Only very few tools for converting English to BSL exist. One of them is *WeCapable* which offers a translator that takes an English sentence specified by a user and converts it into static pictures depicting individual letter signs (Kumar, 2023). While this tool may be useful for learning how to fingerspell,⁴ it cannot translate into glosses. Furthermore, as the letter signs provided are in the form of pictures rather than videos, dynamic signs may be hard to interpret, potentially generating ambiguity for the user.⁵ The translation tool of WeCapable also makes no attempt to convert an input English

sentence to BSL syntax. It simply takes the user input and returns a letter-by-letter translation of each word in the order that they were entered in.

Sign Translate (Moryossef, 2023) is a web application, similar in appearance to Google Translate, that presents the translation output using an avatar that performs dynamic signs. However, selecting "United States" as the target language (i.e., American Sign Language) produces an output that is a sequence of alphabet signs, spelling out each word in the input (similarly to WeCapable). Setting the target language to "United Kingdom" (i.e., BSL) leads to a slightly confusing output, with the avatar not spelling out the words, but instead providing a dynamic output with seemingly little or no relation to the input English sentence. As a whole, this tool also does not make any attempt to convert the input to the correct BSL grammatical structure.

Signly differs from the previous two translation tools in that, rather than a stand-alone web application, it is a module that can be integrated into existing websites (Signly, 2023). Organisations can register with Signly to add sign language translation to their sites. Professional sign language interpreters are hired to record the BSL translation for each section of text in a given website. Signly thus provides English-to-BSL translation as a service, one that is more accurate than can be achieved via any automated translation. However, this cannot be done in real time and the domain of translation is limited to text on registered websites. Each time a company that uses Signly updates its website, an interpreter must manually sign any new text.

Our proposed work is different from the abovedescribed existing tools for English-to-BSL translation, in seeking to provide real-time translation for user-specified inputs, and importantly, in generating translation outputs that follow the BSL grammatical structure.

3 The BSL Grammatical structure

Understanding the fundamental grammatical structure of BSL is imperative when attempting to perform sign translation. This section provides a brief overview of the linguistic features of BSL.

Each individual sign can be represented by a *gloss*. Glosses are lexemes, meaning that they remain constant regardless of any modifications to the word in English. This is because BSL is agnostic to any inflectional changes. There are no tenses in BSL, thus the English words "*eat*", "*eating*"

⁴Fingerspelling refers to signing sequences of alphabet letters comprising either full words or abbreviations (Brown and Cormier, 2017).

⁵For example, the letter *H* is a dynamic sign where the palm of one hand is swept across the other — this would not be clear from a static image.

and "*ate*", for example, are all encompassed by the gloss "*eat*", and therefore share the same sign in BSL (Fenlon et al., 2015). Notably, glosses can represent phrases or emotions as well as individual words.

BSL developed independently of spoken English, so it naturally follows a different grammatical structure. Deuchar (2013) analysed the observable grammatical structure of BSL and how it differs from spoken English. However, they note that due to a significant lack of research into the linguistic structure of BSL, there is no official codified grammar. Despite this, through analysis of organic BSL communication, an overarching summation of the general structure of sentences in BSL grammar can be defined as: 'time-frame then topic then action or a comment'. For example, the English sentence "I ate a cake yesterday" becomes ["yesterday" (timeframe), "cake" (topic), "eat" (action)] in BSL. As one can observe, glosses in the BSL translation follow an order that is different from that of the tokens in the English sentence.

It is also worth noting that certain English words are completely omitted in sign language; intermediary words like determiners, prepositions, and some pronouns do not have a corresponding BSL gloss. Instead, the meaning of these words is expressed via contextual signs and facial expressions. In fact, context cues are crucial in comprehending BSL as a whole. For example, a 'thumbs up' sign can mean "good" or "fantastic" depending on the level of expression. Mouthing specific words, such as nouns and verbs, whilst signing them is also useful, as lipreading is often necessary to discern between different words with similar signs. These nuances can be difficult to replicate via automated translation.

4 Methodology

We decided to take a Rule-Based Machine Translation (RBMT) approach to English-to-BSL translation, whereby a human expert explicitly defines a set of rules (Costa-Jussà et al., 2012). As well as not requiring large amounts of pre-existing data, RBMT systems often provide more control, as the structured design means that results are deterministic and errors are easier to identify (Okpor, 2014). Furthermore, RBMT promotes transparency and scalability, as explicit rules are more easily understood by humans and more rules can be added to improve quality and enhance system complexity.

Our proposed English-to-BSL translation ap-

proach is based on a pipeline with three stages: pre-processing of written English input, rule-based translation and post-processing of output. This pipeline was developed iteratively, leveraging continuous research into the grammatical structure of BSL and personal proficiency in the language.

4.1 Pre-processing

The steps outlined below were implemented and applied to a given English sentence (in the order they are presented):

(1) Contraction expansion: All tokens within a sentence that are detected as contractions (e.g., "don't") were expanded to to their full form (e.g., "do not").⁶

(2) Punctuation removal: A regular expression was used to match and remove all punctuation.

(3) Numeric form conversion: BSL requires that all mentions of numeric values, including those spelt out as words in the input English sentence (e.g., "*eleven*", "*two thousand and twenty three*"), are expressed in their numeric form (e.g., "11", "2023"). We employed a word-to-numbers conversion library⁷ to carry out this transformation.

(4) Tokenisation: Tokens in the sentence (the version that is the result of the preceding steps) are identified by using whitespace as delimiter.

(5) Lowercasing: Each token is lowercased except for the pronoun "I" (as our rules need to be able to identify this pronoun later on, as described in Section 4.3).

The output of the above pre-processing steps (e.g., ["next, "week", "I", "am", "getting", "a", "new", "dog"] for the sentence "Next week, I'm getting a new dog.") is then analysed by our core translation component.

4.2 Rule-Based Translation

The core component of our translation pipeline is underpinned by a Part-Of-Speech (POS) tagger and a set of rules that re-order the tokens resulting from the pre-processing stage.

POS Tagging. The sequence of tokens obtained from the pre-processing stage is analysed by a transformation-based-learning POS tagger,⁸ which was chosen for its speed (i.e., capability to tag over

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<sup>7</sup>https://www.npmjs.com/package/
words-to-numbers
<sup>8</sup>https://www.npmjs.com/package/
wink-pos-tagger
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⁶Using the library available at https://www.npmjs. com/package/expand-contractions

525,000 tokens per second) and accuracy (93.2% on the WSJ22-24 benchmark dataset (Marcus et al., 1999)). This POS tagger produces its output following the Penn Treebank tagset.⁹

Handcrafted Rules. Tokens are ordered by determining where each of them should be placed relative to the other tokens, based on the order expected in BSL. The rows of Table 1, when read from top to bottom, indicate the order in which tokens falling under different word classes (as specified by POS tags) should appear in the BSL translation of an English sentence.

In handling certain word classes, we handcrafted a number of rules, outlined below.

(1) Handling temporal expressions: Words pertaining to time frame (e.g., "next week", "yesterday") should come first in the BSL translation output (except in cases where the English sentence contains interjections). As POS tagging does not identify temporal expressions, we compiled a list of such expressions. Any token that matches any of the expressions in this dictionary is detected as a temporal expression, and thus considered to be the time frame of the sentence.

(2) Coordinating conjunctions: If a coordinating conjunction such as "and" is used to join multiple clauses (as in the sentence "Her name is Mary and she likes to eat cake"), the sentence is split into its individual clauses, each of which needs to be translated separately (i.e., as if each clause is a sentence). However, the sentence should not be split if the conjunction is used to join multiple items (as in the sentence "Mary likes cats and dogs"); this can be determined by checking if the POS tags of the tokens on both sides of the conjunction are the same.

(3) Tokens belonging to commonly used bigrams: A dictionary of commonly used token bigrams was compiled. These include phrasal verbs (e.g., "*pick up*", "*come back*") as well as the combination "I am". If a token bigram in a given sentence matches any of the entries in our dictionary, they are kept together in the re-ordered token sequence.

(4) Handling names of months: In BSL, signs for names of months are represented by the first three letters; for example, the month "*October*" should be converted to the gloss sequence ["O", "C" and "T"]. Thus, a rule was introduced so that a token

corresponding to the name of a month is converted to a sequence consisting of its first three characters.

After re-ordering based on the above rules, the token sequence ["next", "week", "I", "am", "getting", "a", "new", "dog"] becomes ["next, "week", "a", "new", "dog", "getting" "I", "am"].

4.3 Post-processing

The sequence of tokens resulting from our rulebased re-ordering method is processed by the following post-processing steps, in order to finally generate a sequence of BSL glosses.

(1) Stopword removal: We curated a stopword list that consists of words that are not utilised in BSL, e.g., determiners ("a", "an", "the"), pronouns and a selection of verbs (such as "am", "do", "did", "could", "should" and "would"). Tokens in the sequence that match any of the stopwords are removed. It is important to note, however, that the pronoun "I" is handled as a special case: if it is part of the token bigram "I am", the bigram is converted to the gloss "me". If it, however, appears on its own (as in the sentence "I ate a cake"), then it is considered to be a stopword that is then removed.

(2) Lemmatisation: To convert each remaining token to its corresponding BSL gloss, we utilised a dictionary-based lemmatiser¹⁰ to retrieve the lemmatised form (also known as lemma or baseform) of each token.

Upon post-processing the re-ordered sequence ["next, "week", "a", "new", "dog", "getting" "I", "am"], for example, the sequence of glosses ["next, "week", "new", "dog", "get" "me"] is generated as the output BSL translation.

5 The English2BSL Web Application

In order to facilitate user interactivity and display the English-to-BSL translation generated by our rule-based system, a novel web application, *English2BSL*,¹¹ was developed. The Angular framework¹² was utilised in integrating the translation pipeline into the user interface.

5.1 Building a Collection of Sign Videos

As discussed in Section 1, we seek to provide the final BSL translation output in the form of a series of sign videos, each representing a BSL gloss. To this end, we built a collection of sign videos. The

¹⁰https://www.npmjs.com/package/

⁹https://www.ling.upenn.edu/courses/ Fall_2003/ling001/penn_treebank_pos.html

lemmatizer
 ^{II}https://english2bsl.vercel.app/

¹²https://angular.io/

Word Class	POS Tags
Interjections	UH
Temporal expressions	-
Determiners	DT
Prepositions	IN
Adjectives, Numbers, Possessive pronouns	JJ, JJR, JJS, CD, PDT, PRP\$
Nouns	NN, NNP, NNS, NNPS
Foreign words	FW
Verbs, Adverbs	VBD, VBG, VBN, VBP, VBZ, VB, RB, RBR, RBS
Existential there, Modals	EX, MD
Pronouns	PRP
Question words	WDT, WP, WP\$, WRB

Table 1: The rows from top to bottom indicate the order in which glosses should appear in a BSL translation. The POS tags shown follow the Penn Treebank tagset. Temporal expressions are detected using a dictionary-based method.

first author of this paper recorded sign videos in one sitting (with the same background and lighting conditions) to provide consistency throughout the video collection, and ensure that transitions between videos (when put together in a sequence) are as seamless as possible. Our collection contains a total of 213 videos, spanning 273 most commonly used glosses. It is worth noting that this video collection is available in the form of a BSL sign dictionary¹³ as part of the English2BSL web application.

Given a sequence of BSL glosses generated by our rule-based approach, videos depicting signs that correspond to each gloss are played in sequence by the application, as shown in Figure 1. A length limit of 45 characters is applied to the user-specified input English sentence. This is to encourage users to provide sentences that are not too complicated and are easy to understand when signed in BSL.



Figure 1: A still from an example video output displayed by English2BSL in real time, based on the sequence of BSL glosses generated by our rule-based translation approach.

Considering that our sign video collection is not

complete (in that it does not include every possible sign), it is inevitable that certain glosses in the BSL translation output are out of vocabulary, i.e., sign videos for some glosses might be missing in our collection. English2BSL handles such cases by displaying a series of videos that show how to fingerspell an out-of-vocabulary word, as shown in Figure 2.



Figure 2: An example video output displayed by English2BSL where one of the glosses, "*poodle*", is out of vocabulary and is signed by fingerspelling.

5.2 Spelling Correction Suggestions

To make the application more user-friendly, automatically generated spelling correction suggestions were incorporated. Firstly, a dictionary of lemmas corresponding to the 273 glosses in our video collection was compiled and then expanded so that all possible inflectional forms of each lemma are also included. Potential spelling errors in the input English sentence are then detected by checking if any of the input words do not exist in the above-mentioned dictionary. In the sentence "*I like eatin cake*", for example, the word "*eatin*" will be detected as having a spelling error. In contrast, "*eating*" will not be flagged up as an error since it is an inflectional form of "*eat*", one of the glosses in

¹³https://english2bsl.vercel.app/ signdictionary

our sign video collection.

To generate a correction suggestion for a misspelt word, we employed two string similarity algorithms, Dice's coefficient (Robertson and Willett, 1993) and Levenshtein distance (Lhoussain et al., 2015), to identify the lemma or inflectional form in our dictionary that is most similar to the misspelt word. The lemma or inflectional form with the highest string similarity score (according to either of the algorithms) then becomes the correction suggestion. If matches with a similarity score above 0.50 were not found, no corrections are returned to avoid unhelpful suggestions from being generated; the misspelt word is then handled as an out-of-vocabulary word.

6 Evaluation

Our English-to-BSL translation system was assessed using a combination of quantitative and qualitative evaluation strategies.

6.1 Quantitative Evaluation

As discussed in Section 2.1, there is a significant lack of data to support the development and evaluation of English-to-BSL translation systems. To the best of our knowledge, datasets consisting of written English sentences with their corresponding BSL gloss translations were not available. For this reason, we created our own dataset.

After comparing various publicly available datasets containing natural dialogue in English, *DailyDialog*, an open-domain English-language dataset,¹⁴ was chosen due to its varied and conversational nature. The first 150 sentences containing 45 characters or less were extracted from this dataset; then, drawing upon the first author's BSL proficiency, each of these 150 sentences was manually translated into the corresponding gloss sequence based on correct BSL syntax.

Our rule-based English-to-BSL translation approach was applied to each of the test sentences. Comparing the automatically generated translations with the manually generated ones (based on exact matching), an accuracy of 90% was obtained, with 135 of the 150 test sentences having been correctly translated.

6.2 Qualitative Evaluation

Complementing our quantitative evaluation are two User Experience (UX)-based qualitative methods, i.e., user focus groups and expert heuristic evaluation. These were chosen to explore the 'lived experiences' of users and help capture the subjective and contextual aspects of their interactions with the web application.

A focus group of six university students with varying levels of BSL proficiency was conducted alongside expert evaluation with a university-level BSL lecturer. The subjective, anecdotal data collected via these UX evaluation methods exemplifies how potential users respond to the English2BSL application. It was collected in a non-controlled manner, such that it can be generalised to real-life settings. The response to the web application was overwhelmingly positive from both potential user and expert perspectives, demonstrating the effectiveness of the rule-based translation system as well as the UX design of the user interface.

7 Conclusions and Future Work

This paper describes the development of English2BSL, a web application that translates written English into BSL in real time. It is underpinned by a rule-based machine translation approach that leverages the output of syntactic analysis, i.e., POS tags, and a set of handcrafted rules to determine the order in which glosses should appear in the BSL output. Quantitative evaluation of our translation approach showed that it can obtain an accuracy of up to 90%.

The English2BSL user interface displays BSL output in the form of a series of sign videos seamlessly put together, thus acting as an interactive tool for people who wish to build or improve their knowledge of BSL.

A limitation of the proposed translation system lies in its reliance on curated dictionaries (e.g., lists of temporal expressions and commonly used token bigrams) as well the finite number of signs in the video collection. Our future work will focus on expanding our dictionaries and on incorporating more signs into the video collection. Moreover, to broaden the reach of our translation tool, we will explore the development of a version of English2BSL that runs on mobile devices.

¹⁴https://paperswithcode.com/dataset/ dailydialog

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