ISSN 1870-4069

A Comprehensive Review of Sign Language Translation Technologies Using Linguistic Approaches

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Abstract. In a society that seeks to be inclusive, communication between the deaf and hearing communities should be a priority, even so, knowledge of sign language between speakers is scarce, so the development of tools that simplify this communication is essential. It is important the development of software applications that allow the translation of Sign Language into a spoken language or in reverse. Most of the approaches display a sign for each word, the result is a signed sentence that significantly differs from the real signed language. Sign languages have their own grammar structure, which led us to analyze them with their own language components, which should be considered in Machine Translation. This paper describes studies that consider the syntactical component in machine sign language translation. We use a common procedure in the description of works in this field, including documents classified into two categories: Rule-based and Corpus-based. The works based on corpus are divided into Statistics and Hybrid Machine Translation, and Neural Machine Translation. It is important to use new technologies such as deep learning and neural networks in sign language translation systems. In addition to considering the different levels of linguistic analysis in translation.

Keywords: Automatic translation, sign language, syntactic translation.

1 Introduction

Deaf individuals use sign languages as their primary means of communication in daily life. There are more than 200 different sign languages in the world [15]. Communication with hearing individuals encounter barriers, primarily due to limited knowledge about sign languages among the hearing community. The study of sign languages has demonstrated that they are complex linguistic systems that allow people to communicate using their hands and vision to establish communication. A translation process is required to convert the spoken language of the hearing person into sign language for the deaf person, and vice versa (sign language to speech conversion). Automatic translation has emerged as a solution to overcome this language barrier by automating the translation process. There are different approaches to address the issue of automatic translation between different sign languages and spoken languages, such as translating sign language to spoken language and vice versa, representing sign languages in written form using videos or avatars, and translation based on rules, statistics, and Machine Learning techniques, which have become widespread in recent years. However, in this document, we will focus only on research works that deal with automatic translation considering linguistic aspects rather than translating word-for-word.

1.1 Motivation

There are many factors that motivate this work, however we must recognize the need to develop computational tools that facilitate communication between the hearing and the silent community. Given the above, the need to disseminate existing work is essential to encourage researchers to develop new technologies and analyzes in this field. There are many isolated works regarding the field of automatic translation for sign language, however, there are also many approaches from which it has been addressed; this work seeks to compile these approaches. Finally, the review of these works seeks to document the final transition of the word-for-word translation carried out for years.

2 Fundamentals of Automatic Sign Language Translation

In this section we will address different concepts associated with the automatic processing of Sign Language.

2.1 Sign Language

Sign Language is a naturally occurring language that developed as results of the need to communicate among the Deaf communities. Sign language is a language that occurs in the visual-gestural modality, this means that it relies mostly on the use of hands, face, and upper torso. Like many other languages, Sign Language has undergone many transformations throughout its history; this essays traces and details the history or the development of sign language [36].

2.2 Machine Translation

Machine translation (MT) involves to translate a text from one language to another without human intervention. Instead of simply translating the text literally, modern machine translation aims to communicate the complete meaning of the original text in the target language. To achieve this, it analyzes all elements of the text and recognizes how words relate to each other. There are different approaches to machine translation that could be grouped into: Rule-based Machine Translation and Corpus-based Machine Translation. The rule-based machine translation could be direct-based (word by word), interlingua-based (independent interlingua representation), or transfer-based (dependent interlingua representation).

On the other side, corpus-based machine translation includes statistical, example-based, hybrid, and neural. Some authors [22] consider Neural Machine Translation as a third main type of machine learning; because of the data needed for training we consider it as a class inside corpus-base machine translation.

Rule-based Machine Translation. This type of translation requires language specialists to develop linguistic rules and dictionaries for specific topics or domains. Rule-based machine translation utilizes these resources to accurately translate specialized content. The process consists of the following steps: first the machine translation software analyzes the input text and creates an intermediate representation; second, using the grammatical rules and dictionaries as references, the software converts the intermediate representation into the target language.

Corpus-based Machine Translation. Corpus-based approach n (also referred as data driven machine translation) automatically extracts the knowledge by analysing translation examples from a parallel corpus built by human experts. The corpus-based approach is classified into the following sub-approaches:

– **Statistical Machine Translation.** Unlike rule-based translation, this type of translation uses Machine Learning (ML) techniques to translate texts. ML algorithms examine large amounts of previous human translations in search of statistical patterns. Then, when faced with a new source text, the software makes an intelligent guess on how to translate it. This is achieved by making predictions based on the statistical probability of a specific word or phrase appearing next to another word or phrase in the target language.
– **Hybrid Machine Translation.** Hybrid machine translation tools employ multiple machine translation models within a single software system. The hybrid approach is utilized to enhance the performance of a single translation model. This method typically integrates rule-based and statistical machine translation subsystems. The ultimate translation output is a combination of the outputs from all subsystems [3].
– **Neural Machine Translation.** Neural machine translation harnesses the power of artificial intelligence to acquire language knowledge and enhance it iteratively through a specific machine learning technique known as neural networks. It frequently collaborates with statistical translation methods to achieve its objectives.

2.3 Machine Translation for Sign Language

According to Yin [33] the translation of Sign Languages comprises at least the following tasks: detection, identification, segmentation, recognition, translation, and production. The most advanced studies on Sign Language Translation include the detection task that refers to identifying which sign language is being used. However, we must consider that most of the work carried out in this sense is carried out in isolation for specific Sign Languages. Sign-by-sign translation marked the first steps of automatic sign language translation. The most common was to assign a previously marked label to each sign. This label, which we call a gloss, is a specific transcription of each sign in sign language. The gloss is a notation mechanism to facilitate the representation of signs for study.

2.4 Analysis of Linguistic Levels

Linguistics, as a field of study, encompasses five main branches: phonology, morphology, syntax, semantics, and pragmatics. These branches represent distinct areas of language analysis, each focusing on specific aspects of communication.

- **Phonology** refers to the study of the sounds of a language. Every language has a set of sounds and logical rules for combining those sounds to create words. The phonology of a language refers to sounds and the processes used to combine them in spoken language.
- **Morphology** is the study of the internal structure of the words of a language including suffixes, prefixes, or infixes to create new words. The morphology of a language refers to the word-building rules speakers use to create words.
- **Syntactic** is the study of sentence structure. Any language has its own rules for combining words to create sentences. The syntactic analysis describes the rules that speakers use to put words together to create meaningful phrases and sentences.
- **Semantics** is the study of meaning in language. Linguists attempt to identify how the speakers of a language discern the meanings of words in their language and the logical rules speakers apply to determine the meaning of phrases, sentences, and paragraphs. The meaning of a word can depend on the context in which it is used.
- **Pragmatics** is the study of the social use of language. A linguistic analysis of pragmatics can describe the social aspects of the language sample being analyzed.

3 Methodology

The paper focuses on automatic translation at the syntactic level of sign languages. Discarding from the literature those that remain in the morphological component, since it refers to a word-for-word translation ignoring the syntactic structure of the languages. It should be noted that no automatic translation works in sign language were found considering the semantic and pragmatic components since the approach described in Section 5.1.

The phonological component is discarded because it is related to the execution of the sign, that is, the gloss; At this level, the signs typically captured from the video are recognized; at the other end of the translation, the gloss allows the generation or reproduction of the sign through avatars or images. It is important to denote the deep work in this area. There is a recent increase in research in this regard, including mainly neural networks.

Researchers use traditional Neural Networks like feed-forward back propagation network [34], but also new approaches like CNN for the sign recognition like [8] with two CNN, [1] uses CNN and LSTM, and others [31, 27] use RNN like LSTM and GRU. For the sign generation Advesrsalial Neural Networks [51] and GAN [54, 35] have emerged.

Table 1. Corpora comparison.

Corpus Name / Work Title	No. Sentences	No. Words	Languages Involved
RWTH-PHOENIX - Weather	1980 in DGS, 1489 in German	911 in DGS, 1489 in German	German Sign Language German
ISLTranslate	31k	11k	Indian Sign Language-English
ASLG-PC12	Over one hundred millions of pairs sentences	-	American Sign Language-English
Multimedia Corpora of Mexican Sign Language (MSL) with Syntactic Function	-	1505 words in Spanish related to 1019 videos of signs	Spanish-Mexican Sign Language
Translating Speech to Indian Sign Language Using Natural Language Processing	A video DB created by the authors. The DB contains 1000+ videos and open-source ISL videos	-	Indian Sign Language - English
Linguistic Restrictions in Automatic Translation from Written Spanish to Mexican Sign Language	-	206 signs with synonyms and 1790 signs from Manos con voz Mexican Sign Language dictionary	Spanish-Mexican Sign Language.
KArSL	-	502 signs that cover 11 chapters of ArSL	Arabic Sign Language
LSE-Sign	-	2,400 individual signs taken from standardized LSE dictionary	Spanish Sign Language
ISL-CSLTR	100 spoken language sentences	1036 word level images	Indian Sign language - Indian
ASL-LEX	-	nearly 1000 signs	American Sign Language

4 Sign Language Datasets

The creation of a spoken language to sign language translator faces significant challenges in obtaining sample translation examples. Limited interpreter availability, scarcity of sign language studies, and substantial grammatical differences between spoken and sign languages contribute to this difficulty.

Moreover, the lack of standardization poses a challenge, as different sign languages may have distinct grammatical rules. Another challenge arises from segmenting sentences in sign language, which requires expert sign language proficiency to accurately identify the start and end of signs. This often necessitates manual frame segmentation in datasets, particularly in videos with sign language interpreters, requiring the assistance of a sign language expert. The demanding nature of this task, along with the need for numerous examples, makes dataset collection labor-intensive and costly. The Table 1 shows a description of some of the corpora used for translating spoken language to sign language.

5 Natural Language Processing in Automatic Sign Language Translation

Natural Language Processing (NLP) is a discipline that studies language issues in human-to-human and human-to-machine communication [5]. It studies Automatic Translation, also known as Machine Translation, at the different language levels or components wich are describe in the next section. We focus this study on Syntactic and Semantic levels for Automatic Sign Language Translation.

5.1 Language Components and Translation in Sign Language

Language components are phonology, morphology, syntax, semantics, and pragmatics. We identify those components in sign language. We focus on Mexican Sign Language (MSL) for the examples.

Phonologic Component. Sign languages have no phonemes but we can do an analogy for the phonological component. Oral languages consist of a series of successive sound elements, while visual signs have a series of simultaneous constituents. It has [48]:

- Queiremas: Involves hands and finger positions, this is the one that most people identify.
- Toponemas: The 25 body zones where the sign is done. For example, the sign of pain usually points to the body part that hurts:
- Kinemas: 18 different movements and the number of times those are done. For example, the sign of person involves one movement from top to bottom but if the sign is plural (persons) the movement is done three times.
- Kineprosemas: 6 directions of the sign. For example, the sign of help has a different movement depending on who gives and who receives the help.
- Queirotropemas: There are 9 different palm orientations.
- Prosoponema: Involves facial expressions.

According to the tasks of the translation of Sign Languages proposed by [33], this phonological component has to be identified when doing a translation from signs to oral language; also, it is obtained for the production of the sign when doing a translation from oral to sign language.

Table 2. Classification of works by the type of automatic translation.

Type of Machine Translation	References
Rule-base Machine Translation.	[17, 58, 60, 49, 11]
	[4, 30, 46, 2, 45]
	[13, 12, 44, 37, 25]
	[29, 19, 26, 56]
Corpus-based: Statistical and Hybrid Machine Translation.	[59, 39, 53, 50]
Corpus-based: Neural Machine Translation.	[55, 8, 32, 54, 6]

Morphologic Component. A sign is the union of a concept and an acoustic image. A morphological analysis gives a direct translation where each word is represented by a sign, or each sign is represented by a word. Translation at this level gives signed sentences, that do not consider the syntactic structure of both languages and is the most common in literature [1, 24, 57].

Nevertheless, it has some challenges for translation. Oral languages usually have much more words than signs in sign languages; then, words are represented by several signs. Two main cases are compound signs and lexical-visual paraphrases. The first one joins two or more signs to express a concept, for example, the word weekend uses the signs saturday+sunday. The second one describes the concept by several signs, for example, the word burrow is represented by the signs: hole+exactly+home+rabbit.

Syntactic Component. Translation at the morphological level gives signed sentences. That is a word-to-word translation or direct translation. Those word sequences need to be arranged considering the grammatical order of each language.

Semantic Component. Spoken languages have a temporal dimension, they are linear, but in gestural sign languages, the expression is based on two coordinates: space and time, where the spatial dimension is dominant. In addition to the phonemes or minimal signifying units; there are kinetic formative parameters that are the articulatory elements that make up the gestural sign with distinctive value. For example, raising eyebrows to denote causality.

There are other deictic elements as a point of reference with elements such as “this”, “there”, or “now”. Moreover, the dominance of the spatial dimension allows the signer to “place” people or things in space and then use them by modifying the direction of the signs (kineprosema). For example, if the phrase is: “The antenna sends a signal to the cell phone”, the signer first makes the “antenna” sign and “places it spatially” to the right at the top, secondly he makes the “cell phone” sign ” and places it to his left, then he does the sign of “signal” and moves it from right to left joining the first two invisible elements that were placed.

Something similar happens when stories are told, the signer places the interlocutors and turns his back so that he takes the role of one or the other to demonstrate the orientation of the communication between the interlocutors. Reaching this level of translation between two spoken languages is difficult; and even more so when we have sign languages.

5.2 Machine Translation at the Syntactic Level in Sign Language

Machine translation is the use of the computer to realize automatic translation between different languages, from a source language to the target language. It includes data mining and cleansing, word segmentation, part-of-speech tagging, and syntactic analysis [20]. There are two main types of machine translation: rule-based machine translation and corpus-based machine translation (see Section 2.2).

Table 2 shows the studies analyzed in this review. The following sections uses this classification to describe those works. Sign Language Translation requires finding a mapping between a spoken and signed language, that takes into account both their language models, which correspond to the syntactic level.

There are several successful machine translation systems implementing NLP but sign language machine translation has not been widely explored. 28 papers were analyzed that consider the syntactic component of language. Most of the works focus on American Sign Language, also the works using German Sign Language have increased because of the publication of a corpus [8].

Followed by Spanish, Arabic, Spanish and Mexican Sign Language. Other sign languages included in this review are: Swiss German Sign Language, British Sign Language, Pakistan Sign Language, Indian Sign Language, Taiwan Sign Language, Thai Sign Language, Vietnamese Sign Language, Chinese Vietnamese, Ukrainian Sign Language, Portuguese Vietnamese and Italian Sign Language.

Rule-Based: Interlingua and Transfer-Based Machine Translation. The rule-based machine translation includes direct-based, interlingua-based, and transfer-based. Once we focus on the syntactic level, we do not consider the direct-based translation for this study. As it has been said, the problem is not simply mapping text to gestures word-by-word. Most of the rule-based studies focused on rigorous analysis of the grammar of the sign language to define the translation rules, because usually sign languages do not have a formal definition on their countries.

A previous stage of rule-base translation is pre-processing, which allows to prepare the text before the translation stage using tokenization, lemma extraction, and tagging, among others. Some works tokenize the text into words [4, 2], n-grams [44], or sentences [11]. The syntactic analyzer [49, 4, 46, 44] identify the syntactic components of a sentence, such as subject and object. Sign languages, typically, do not consider some syntactic components like prepositions, conjunctions and others so they have to be eliminated as a pre-stage [37, 45] or at the moment of translation [4, 30].

For rule-based translation, some authors just reorder the syntactic components [11, 46, 2, 19], most of the authors did a deep search or analysis of the Sing Language, and obtain a sequence of rules to transform the text into gloss, mainly grammar conversion rules [49, 4, 45, 13, 37, 25, 26, 56]. Other works create an intermediate representation [58, 12, 17], the intermediate representation could include ontology like the semantic ontology of [30] or syntactic trees like [60] with their Synchronous Tree Adjoining Grammar (STAG), and [44, 29] using syntactic trees.

Corpus-Based: Statistical and Hybrid Machine Translation. The corpus-based machine translation could be classified as statistical, example-based, hybrid, or neural. Corpus-based mainly use data sets; Because of the lack of data sets on sign languages, there are fewer studies.

The next section deals with Neural Machine Translation, while in this section we cover the other classes. Wu et al. [59] transform the sentences to possible phrases structure trees from two sets of probabilistic context-free grammars with their own rules. Another work that generates its own grammatical corpus is [39], they build an artificial corpus using grammatical dependencies rules, which is used as input of a statistical machine translation.

Stein, D., Bungeroth, J., and Ney, H. [53] uses phrase-based statistical machine learning on a new corpus of weather reports enhanced by pre and post-processing steps based on the morpho-syntactical analysis of German. Hybrid Machine Translation is uses by [50], they combine statistical translation with an example-based strategy and a rule-based translation method.

Corpus-Based: Neural Machine Translation. Neural machine translation (NMT) is a newly emerging approach to machine translation [23, 28]. The models proposed recently for NMT often belong to a family of encoder-decoders and consist of an encoder that encodes a source sentence into a fixed-length vector from which a decoder generates a translation.

ATLASLang [6], an automatic translation system from Arabic text to Arabic Sign Language (ArSL), uses a backpropagation neural network and focuses on translating simple sentences made up of a limited number of words. A database of signs and morphological characteristics was used to improve the translation. A novel transformer-based architecture is proposed in [9], which jointly learns Continuous Sign Language Recognition and Translation in an end-to-end manner.

By using a Connectionist Temporal Classification (CTC) loss, the recognition and translation problems are combined into a unified architecture, without requiring ground-truth timing information. The approach achieves significant performance gains and outperforms previous translation models on the PHOENIX14T dataset. From the same teamwork, other proposals have been developed.

In [55, 54] they use Neural Machine Translation and Image Generation techniques within three key stages: Text-to-Gloss Neural Machine Translation (NMT) Network, Gloss-to-Motion Lookup Table, and Pose-Conditioned Sign Generation Network. The first one considers the syntactic component; it employs an RNN-based machine translation method using an encoder-decoder architecture with Luong attention for translating spoken language sentences to sign glosses.

6 Challenges and Future Directions

The scarcity of data in sign language translation poses significant challenges due to the vast diversity of sign languages, their lack of standardization, and the limited attention given to deaf individuals. Acquiring extensive datasets is costly and time-consuming, prompting the exploration of alternative approaches that can work effectively with reduced datasets. To address the limitations of Deep Learning models with limited training data, Few-Shot Learning emerges as an approach to learn underlying patterns with just a few training samples. This offers a less expensive solution compared to training large-scale Deep Learning models, which require substantial computational resources and time [41].

Long Language Models (LLMs), such as the LLM GPT-3.5, have demonstrated remarkable capabilities in Natural Language Processing (NLP) tasks, including translation. Scaling up LLMs has shown to greatly enhance task-agnostic, few-shot performance, sometimes outperforming prior state-of-the-art fine-tuning methods [7]. Utilizing the OpenAI API, the LLM GPT-3.5 can be employed and fine-tuned with specific datasets [38], even for tasks like translating from spoken language to sign language gloss. This approach eliminates the need for excessively large datasets, making it a viable option for effective translation.

7 Conclusion

Text to Sign Language Translation has been a widely researched area among various communities worldwide working for the betterment of deaf societies. After reviewing more than 100 articles we have selected 33 published studies. The papers were classified according to different types of machine translation systems, sign language generation methods, and evaluation metrics used. The approach of the present work considerably reduces the articles included since only those that developed a translation that included artificial intelligence techniques and that considered an integral translation at the syntactic level not with signed languages were considered.

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