

# Recognizing 3D skeletons with sign language graphs

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## Abstract

It is difficult to analyze and understand 3D data for machine interpretation. In this work, we suggest utilizing Graph Matching (GM) for sign identification based on 3D motion collected ISL data. We formulate the sign identification and categorization issue using 3D motion signs as an AGM. However, there are significant limitations with the present models, the most notable of which are (1) spatial matching on a defined set of frames with fixed nodes and (2) temporal matching breaking the full 3D dataset into fixed pyramids. These issues are addressed by our method, which employs spatial matching between frames and temporal matching for numerous intra-frame matches. A 3D sign language dataset consisting of 200 continuous phrase signs was captured using an 8-camera motion capture setup to evaluate the proposed model. We demonstrate that our method improves the reliability of sign recognition in ongoing sign language discourse.

## 1.Introduction

Hand and finger movements in sign language are intricate and non-linear. In addition, the body parts of the head and the torso are sometimes mentioned when elaborating on a specific symbol. Research into machine translation of sign language focuses on two main areas: instrumentation and signal processing, and computer vision. As for the first part, a pair of sensor gloves is employed; the wearer's finger movements generate 1D vectors for categorization. The second part has to do with a 2D camera sensor. As far as processing performance is concerned, we find that 2D time-varying techniques are preferable than 1D ones. Sign language is a visual language model because it relies on hand shapes and gestures in addition to those involving the face, head, and body. While the sensor-glove based method can decipher signs including hand movements in relation to the head, face, and torso, it cannot decipher signs involving hand motions alone.

In order to get the QSFs from the CSFs, an adaptive graph matching (AGM) approach is proposed. For a series of QSFs or CSFs, IGM determines the degree of similarity between

pairs of adjacent vertices and edges. However, due to the negligible differences between signs, the IGM model typically results in negative matching when applied to 3D data pertaining to sign language. An AGM model is used to address this issue. Each QSF and CSF vertex and edge are time and space matched in this model. In order to locate the indicators in the CSF dataset, first temporal matching is performed.

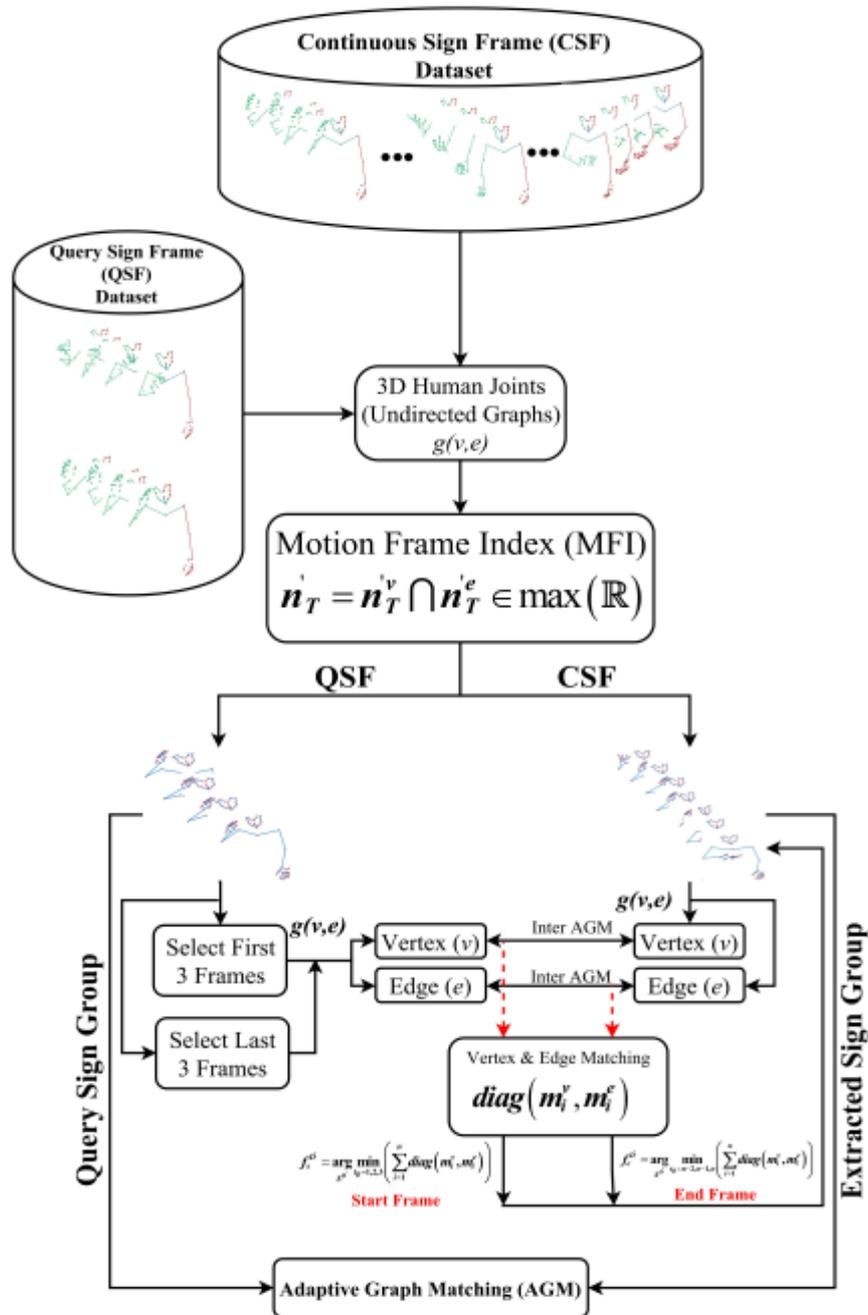


Fig. 1: Flowchart for the proposed 3D SLR process

The initial three frames of the QSF and the last three frames of the CSF dataset are subjected to AGM. Matching locations in the CSF dataset are provided here. Each of these coordinates is associated with a beginning and an ending frame from the CSF database. The frequency with which a certain QSF might appear in the CSF dataset allows us to acquire various beginning and ending frames. When matching the QSF, a spatial AGM is used to group together the various CSFs into a single group CSF (GCSF). The vertices and edges of each spatial graph in the QSF are paired with their corresponding graphs in the GCSF. That's why our proposed spatial AGM works with any size of QSF or GCSF, not just fixed numbers. The proposed workflow for 3D SLR is depicted in Figure.1.

## **2. GM in 3D for SLR**

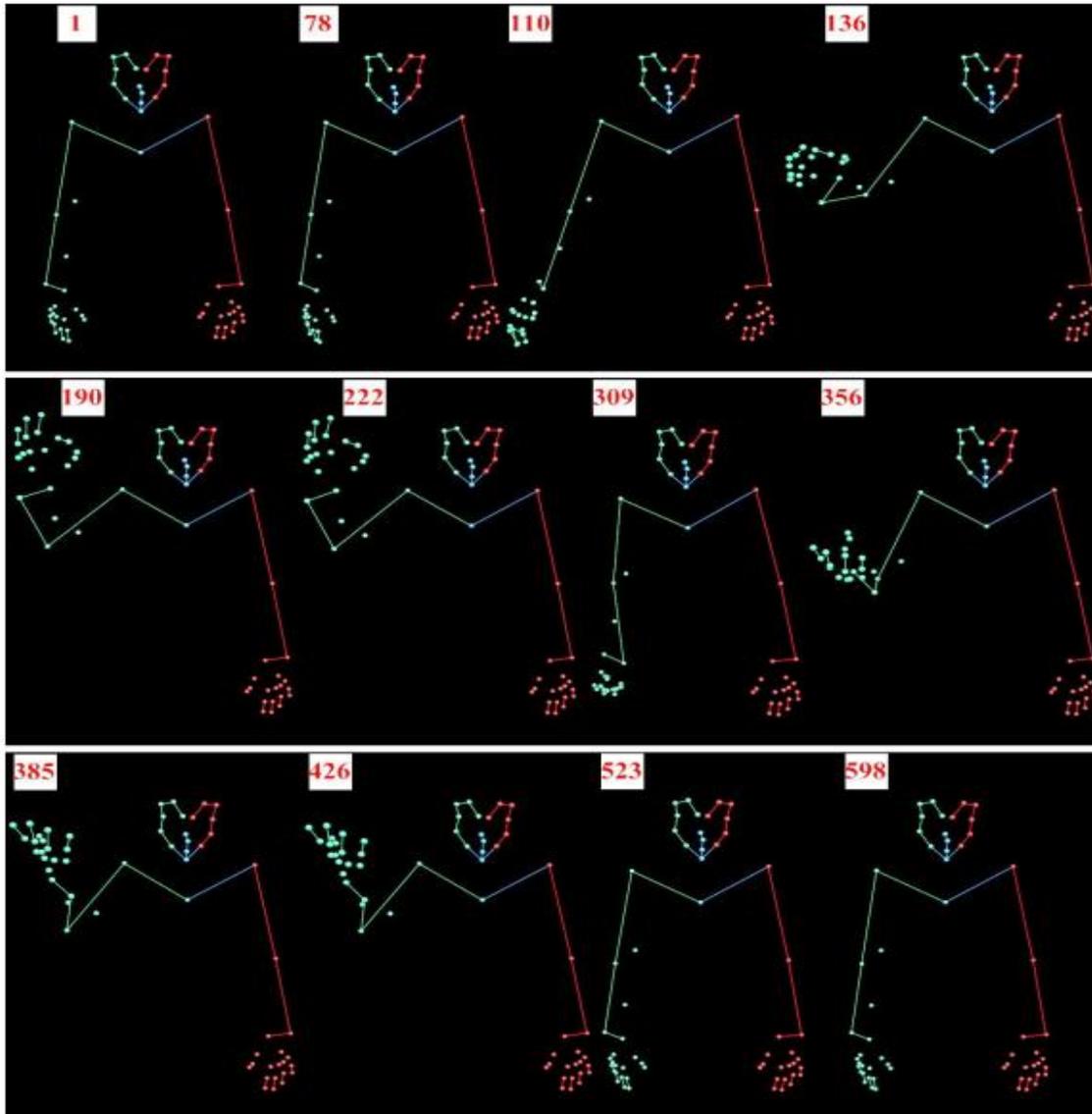


Fig. 2: "Good Morning" sign recorded in 600 frames with the intermediate rigid and changing frames with frame numbers

A framed image of the "Good Morning" sign from the CSF dataset is shown in Figure.2. Because intraGM was applied to the complete 3D dataset, the motion segmentation issue manifests itself in the spatial dimension of the data. Similarity in hand motion and shape relative to head, face, and torso recognition in the dataset can be accurately modeled by using all available vertex and edge matching. The GM procedure followed in this analysis can be seen in Figure.3.

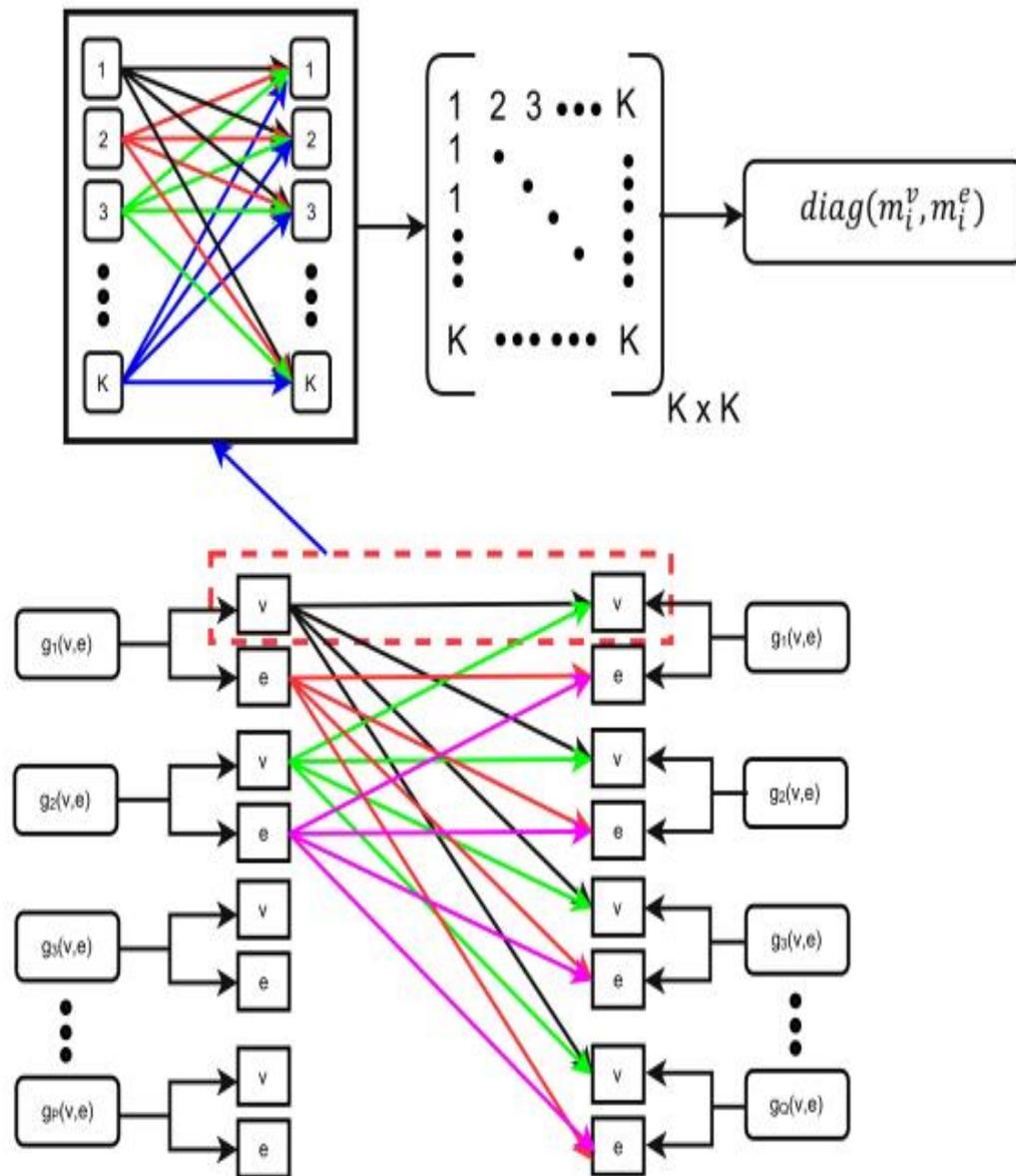


Fig. 3: AGM visualization for sign similarity matching.

### 3. Conclusion

This research proposes the difficult but worthwhile endeavour of automating sign language. Three-dimensional Indian sign language symbols are catalogued. Undirected graphs are utilized to create and express signs, with 3D position trajectories serving as features. The procedure began with the creation of a 3D signer's template that can accurately represent all the signs used in Indian sign language. The sign data is run through a combination of motion

segmentation and AGM algorithms to enable recognition and text conversion. Two areas where prior GM models for sign language fell short and where the proposed AGM excels are in form extraction and relative frame extraction. This greatly enhances the precision of matching in continuously playing films for the purpose of recognizing and identifying signs in real time. With AGM applied to 3D motion capture data, we find that the TWRF is close to 100% for the signals we test. However, the proposed model's processing needs to be reduced so that real-time recognition is possible.

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