

GREEK SIGN LANGUAGE RECOGNITION FOR THE SL-REDU LEARNING PLATFORM

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Overview

Goal:

- ✓ SL education tool development for SL production self-assessment and objective evaluation.
- ✓ SL recognition (SLR) from videos in a signer-independent (SI) mode under realistic recording conditions.

Previous work [1, 2, 3]:

- ✓ A suitable platform for the SL-ReDu project is built involving "passive"-type GSL learning exercises.

SL recognizer:

- ✓ Recognition module based on state-of-the-art deep-learning techniques.
- ✓ Focus on isolated signs and continuously fingerspelled letter sequences.

Contributions:

- ✓ Early version of a GSL recognizer integrated within the SL-ReDu learning platform.
- ✓ First education tool in GSL with recognition functionality.

Evaluation:

- ✓ High multi-signer (MS) and SI recognition accuracies.
- ✓ Evaluation by student and expert users of the SL-ReDu platform and its recognition functionality demonstrates very satisfactory objective and subjective assessments.

- ✓ Two recognition **subtasks** employing **separate models**:

- **Numeral signs** with a vocabulary size of 18.
- **Non-numeral signs** with a vocabulary size of 36.

Continuous Fingerspelling Recognition:

- ✓ CNN-BiLSTM model is used.
- ✓ MobileNet based visual **feature learner** of each video frame: 1024-dim features.
- ✓ Features are fed to a **linear projection** layer for **size reduction**: 512-dim features.
- ✓ Two-layer **BiLSTM encoder** followed by **CTC decoding**.

GSL Database

Signing data by multiple volunteer informants both native and non-native in GSL:

- ✓ Data recorded indoors, under realistic, **non-studio conditions**.

Numeral signs:

- ✓ 20 signers x 18 signs x 5 times: **1,800 videos**.

Non-numeral signs:

- ✓ 17 signers x 36 signs x 5 times.
- ✓ ITI GSL corpus [4]: 7 signers x 36 signs x 5 times.
- ✓ Total: 24 (17 + 7) signers - 4,320 videos.

Fingerspelling data:

- ✓ 12 informants: 24 Greek **alphabet letters** and **50 fingerspelled words** of 4-5 letters (unique to each signer).
- ✓ 7 informants: **16 3-7 letter words** (common to all).
- ✓ 3 signers expressed **extra 71 words** of 4-5 letters.
- ✓ Total: **1,071 videos**.



(Numerals) (Non-numerals) (Fingerspelling)

Experimental Framework

Multi-signer (MS) recognition:

- ✓ Training **80%** of all **videos** (numerals: 1,440; non-numerals: 3,456; fingerspelling: 857).
- ✓ Validation **10%** of all **videos** (numerals: 180; non-numerals: 432; fingerspelling: 107).
- ✓ Testing **10%** of all **videos** (numerals: 180; non-numerals: 432; fingerspelling: 107).

Signer-independent (SI) recognition:

- ✓ 20-fold cross-validation for **numerals**.
- ✓ 24-folds cross-validation for **non-numerals**.
- ✓ 12-folds cross-validation for **fingerspelling**.
- ✓ Each fold contains **one test subject**, all remaining subjects are used in **training**.

SL-ReDu platform user evaluation:

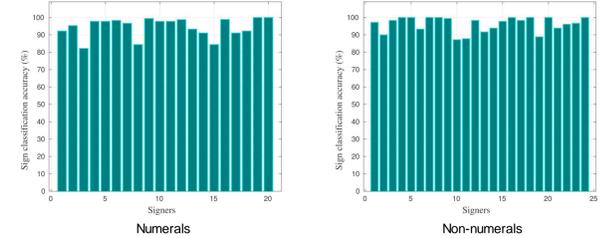
- ✓ Training: **90%** of the available **videos** (numerals: 1,620; non-numerals: 3,888; fingerspelling: 964).
- ✓ Validation: **10%** of the available **videos** (numerals: 180; non-numerals: 432; fingerspelling: 107).

GSL recognition performance:

- ✓ Isolated GSL and continuous fingerspelling tasks under both **MS** and **SI** training/testing cases.
- ✓ GSL recognizer **objective evaluation** results.
- ✓ Results in word accuracy (**WAcc**) %, and in the case of fingerspelling in letter accuracy (**LAcc**) %.
- ✓ **Isolated GSL recognition task**:
 - Performance **degrades** in the **SI** case.
 - **WAcc** satisfactory in **both isolated SLR tasks**.
 - **Objective evaluation: results better than SI case**.
- ✓ **Continuous fingerspelling recognition task**:
 - Performance **suffers** at the **WAcc** level, especially for longer letter sequences.
 - **Higher LAcc** results.
 - **Objective evaluation: results better than SI scenario**.

GSL recog. task	Metric	MS	SI	Eval.
iso. numerals	WAcc	97.78	94.48	98.61
iso. non-numerals	WAcc	99.44	96.20	97.22
cont. fingerspelling	WAcc	75.22	65.30	90.28
	LAcc	86.12	77.66	91.03

- ✓ **SI isolated GSL recognition accuracy (%) per signer for numerals and non-numeral signs**.
- Performance **varies** among signers, **remaining nevertheless well above 80% Wacc**.



SL-ReDu Platform User Evaluation

Volunteer Users:

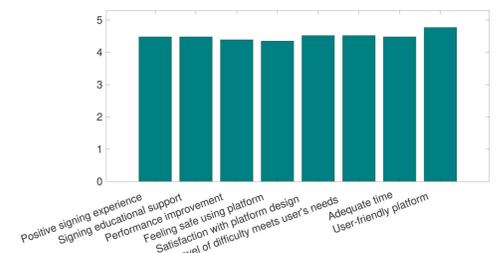
- ✓ Department of Special Education at University of Thessaly students:
 - **Group 1**: 10 students (GSL for less than 5 months).
 - **Group 2**: 11 students (GSL for more than 5 months).
- ✓ **Two GSL experts/teachers volunteers**.
- ✓ **Ages: 19-22 years old / Females > males**.

Objective Evaluation of GSL Recognizer:

- ✓ Evaluation via "**active**"-type exercises requiring SL production by the learner.
- ✓ **Numerals**: 3 assignments of six GSL production questions.
- ✓ **Non-numerals**: 6 assignments of six GSL production questions.
- ✓ **Fingerspelling**: 6 six-question assignments - **Letters** and **words** not in the training set.
- ✓ **Volunteers**: 7 A0 - 4 A1 level students, and 1 expert.
 - Each performs 3 six-question assignments (one per task, totaling **18 questions**).
- ✓ "Active"-type **exams** are automatically **graded** by the system.
- ✓ Results are **better** than **SI recognition** performance of the **isolated/fingerspelling** tasks.

Subjective Assessment of the Platform:

- ✓ Participants: anonymous **subjective experience questionnaire**.
- ✓ Measures **8 aspects** on the one-to-five **Likert scale**.
- ✓ In **half questions** most of the users provided the **highest assessment**.



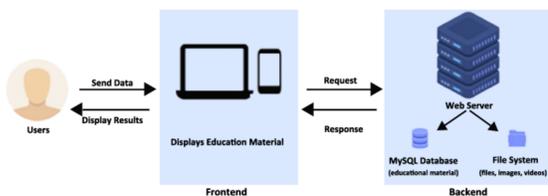
Conclusions

- ✓ Presented the **SL-ReDu learning platform GSL recognizer**:
 - ✓ **Isolated signs** and continuously **fingerspelled** sequences.
- ✓ **Recognition module**:
 - ✓ Incorporates state-of-the-art **deep learning** based visual detection, feature extraction, and classification.
 - ✓ Operates in a **SI** fashion in **non-ideal visual environments**.
- ✓ Designed module **performs very well**, as evidenced by experimental results.
- ✓ Yields **very satisfactory objective** and **subjective** user evaluation of the SL-ReDu platform.

References

- [1] Potamianos et al., "SL-ReDu: Greek sign language recognition for educational applications. Project description and early results," *Proc. PETRA*, 2020.
- [2] Sapountzaki et al., "Educational material organization in a platform for Greek Sign Language self monitoring and assessment," *Proc. EDULEARN*, 2021.
- [3] Efthimiou et al., "The SL-ReDu environment for self-monitoring and objective learner assessment in Greek Sign Language," *Proc. HCI*, 2021.
- [4] Adaloglou et al., "Comprehensive study on sign language recognition methods," *Transactions on Multimedia*, 2022.

SL-ReDu Platform



Enables self-monitoring and objective learner evaluation.

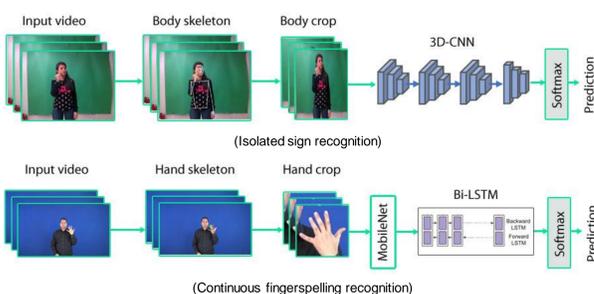
System's design involves all aspects of GSL linguistics:

- ✓ Teaching **techniques** and **content**, including various **SL practice assignments**.
- ✓ **Multiple-choice questions**: images, videos, and text.
- ✓ **User response** or **user feedback** by means of **video recordings** of **GSL production**.
- ✓ Enables the user to **actively sign** and be **assessed** for the capacity to appropriately generate signs.

SL-ReDu prototype system:

- ✓ **Web-based** application managing the **end user's interaction**.
- ✓ **System** modalities entail the system **database**, the **front-end** and **back-end** user interfaces, and image/video **files**.
- ✓ **SLR** is a separate system module **running** as standalone on the **learner's device**.

GSL Recognition Module



Pre-processing:

- ✓ Detect the **signer**, **extract** the Region-of-Interest (**RoI**), and **provide feedback** in case of incorrect **signer positioning**.
- ✓ **MediaPipe** library for signer's **whole-body landmarks** extraction from **RGB video**.
- ✓ **Lack** of detected **landmarks** of hands, face, and upper torso: **incorrect user positioning**.
- ✓ **Correct user positioning: RoI extraction**.
- ✓ **Isolated sign: upper body** is cropped producing the **RoI**.
- ✓ **Fingerspelling: RoI** consists of the **signing hand**.

Isolated Sign Recognition:

- ✓ 18-layer **ResNet2+1D** model is used, separating **spatial** and **temporal convolutions** of 3D CNNs.