





LinguSign

A Bidirectional Romanian Sign Language Translator

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Introduction

- Project inspired by a friend who volunteers with deaf and hard-of-hearing people.
- Currently no automated tool for sign language translation
 difficult communication between deaf and hearing people.
- The tool should be portable and provide real-time bidirectional Romanian Sign Language translation.

The solution is a mobile application that:

- 1. Animates a 3D model to gesture the signs of the spoken words
- 2. Predicts and speaks out loud the recorded gestured signs



MediaPipe

A suite of solutions developed by Google to quickly apply AI and ML.

MediaPipe Hands: extracts the 21 landmarks on the human hand as 3D points.

MediaPipe Pose: extracts the 33 landmarks on the human body as 3D points.

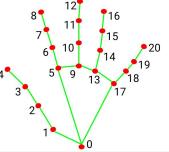
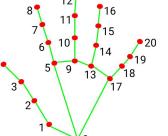


Fig. 1: Hand Landmarks. Accessed: 2024-06-04.



0. WRIST

- 1. THUMB_CMC
- 2. THUMB_MCP
- 3. THUMB IP
- 4. THUMB TIP
- 5. INDEX FINGER MCP
- 6. INDEX_FINGER_PIP
- 7. INDEX_FINGER_DIP
- 8. INDEX_FINGER_TIP
- 9. MIDDLE FINGER MCP
- 10. MIDDLE FINGER PIP

- 11. MIDDLE_FINGER_DIP
- 12. MIDDLE_FINGER_TIP
- 13. RING_FINGER_MCP
- 14. RING_FINGER_PIP
- 15. RING FINGER DIP
- 16. RING FINGER TIP
- 17. PINKY_MCP
- 18. PINKY_PIP
- 19. PINKY_DIP
- 20. PINKY_TIP

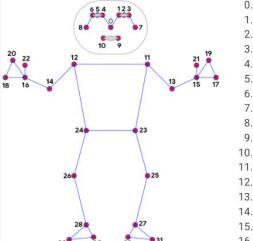


Fig. 2: Pose Landmarks. Accessed: 2024-06-04

- 0. nose
- 1. left_eye_inner
- 2. left_eve
- 3. left_eye_outer
- 4. right_eye_inner
- 5. right_eye
- 6. right_eye_outer
- 7. left_ear
- 8. right_ear
- 9. mouth left
- 10. mouth_right
- 11. left_shoulder
- 12. right_shoulder
- 13. left_elbow
- 14. right_elbow
- 15. left wrist
- 16. right_wrist

- 17. left_pinky
- 18. right_pinky 19. left_index
- 20. right_index
- 21. left thumb
- 22. right_thumb
- 23. left_hip 24. right_hip
- 25. left_knee
- 26. right_knee
- 27. left_ankle 28. right_ankle
- 29. left_heel
- 30. right_heel
- 31. left foot index
- 32. right_foot_index







Kalman Filter

- Uses inaccurate or noisy measurements to estimate the state of that variable or another unobservable variable with greater accuracy.
- First two measurements initialize the system parameters.
- From the third measurement, it consists of two steps:
 - 1. Prediction step
 - 2. Update step

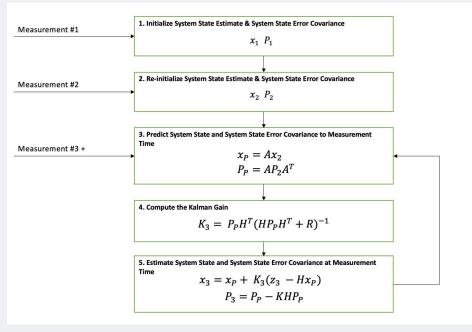


Fig. 3: Kalman Filter Overview. Accessed: 2024-05-29.

• Calculates the unweighted mean of the *m* data points surrounding a central value (including the central value):

$$SMA_n = \frac{1}{m} \sum_{i=-k}^{k} p_{n+i}$$

where m = 2k + 1.

• Efficiently implemented using the convolution operation:

$$(x*h)[n] = \sum_{i=0}^{m-1} x[i]h[n-i]$$

where x is the input data and $h = \frac{1}{m}[1, 1, ..., 1]$ (m elements).





Architecture of the Backend

The backend consists of:

- 1. Web API
- 2. **Database** contains user info and references to resource files
- 3. **Internal NLP service** matches the Romanian words to the constrained RSL vocabulary
- ChatGPT API service builds coherent sentences from given words

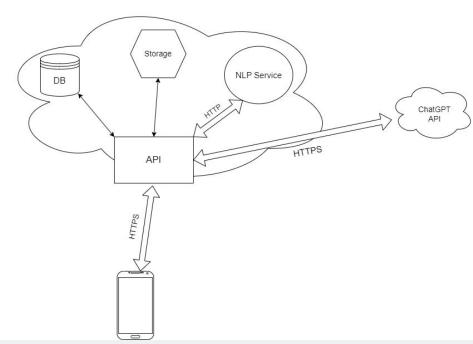


Fig. 4: High-Level Overview of the Backend.







Architecture of the Client Application

1. AnimationFragment

- Performs the RO to RSL translation.
- WordsRecognizer, for each spoken word, sends the list of words spoken thus far to the backend.
- The response consists of the matches in the constrained vocabulary of only the new words.
- AnimationFragment polls the responses queue when ready to animate and applies the filters first.

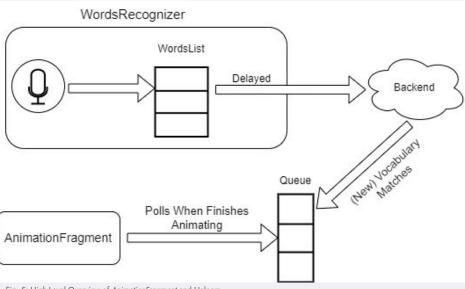


Fig. 5: High-Level Overview of AnimationFragment and Helpers.



Architecture of the Client Application

2. CameraFragment

- Performs the RSL to RO translation.
- Landmarker extracts the landmarks from the camera feed.
- Translator extracts features from the landmarks and enqueues them into a one second window.
- For every frame, the *classifier* is ran on the window. Its prediction is further analyzed for consistency.
- The predicted word is either spoken out loud, or sent along with other words to the backend. The resulting coherent sentence is then spoken out loud.

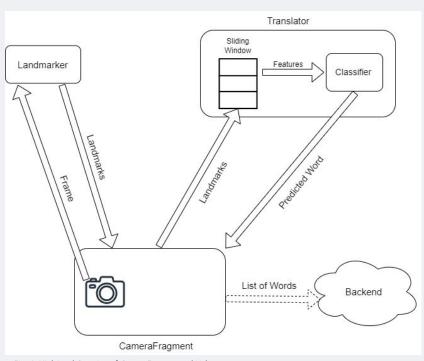


Fig. 6: High-Level Overview of CameraFragment and Helpers.







1. Creating the Constrained Vocabulary

- 1. Scrape videos from https://dlmg.ro/ and https://pesemne.ro/.
- 2. Extract landmarks from the videos using *MediaPipe*.

This is the **vocabulary**.

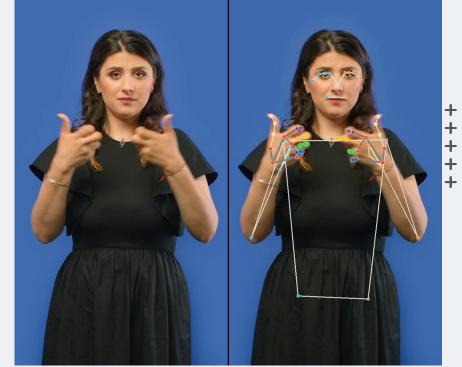
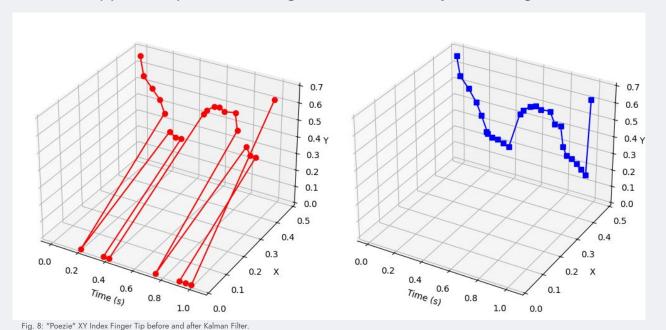


Fig. 7: Frame for the Sign "Examen" before and after Processing.

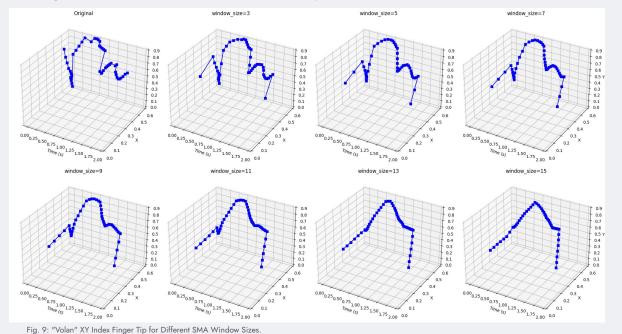
2. Correct the Extracted Landmarks

The Kalman Filter is applied to predict missing landmarks and adjust existing ones.



3. Smooth the Corrected Landmarks

The moving average filter is used to smooth the sequence of landmarks.



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Implementation of the RO to RSL translator

4. Animate a 3D model based on the landmarks

Fundamental technique used to animate the model: Aligning one unit vector (A) to another (B).

$$R_{uvw} = \begin{pmatrix} \cos \theta & -\sin \theta & 0 & 0\\ \sin \theta & \cos \theta & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} A \cdot B & -\|A \times B\| & 0 & 0\\ \|A \times B\| & A \cdot B & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1 \end{pmatrix}$$

The matrix represents the rotation in the following base: C = [uvw]

Where u, v, w column vectors:

- u normalized vector projection of B onto A
- v normalized vector rejection of B onto A
- w normalized cross product of B and A

Final transformation: $C^{-1}R_{uvw}C = C^TR_{uvw}C$





4. Animate a 3D model based on the landmarks

- 1. Extract the initial transformation components from the 3D model to be animated.
- 2. Transform the 3D landmark positions of the video into world coordinates.
- 3. Compute the rotations needed to align the model's T-Pose to the position defined in the extracted landmarks along the kinematic chain.
- 4. Align the hand's extracted landmark's basis to the lower arm's and continue along the kinematic chain to compute the fingers' rotations.





5. The NLP Service

- Takes as input a natural, spoken sentence.
- Returns a list of matches from the vocabulary.
- Matches the words or their lemmas or stems through a heuristic combining the Levenshtein and cosine distances.





1. Creating the Dataset

- Recorded 30 one second videos containing only the main part of the gesture for each sign.
- Extracted the landmarks with MediaPipe.

2. Feature Engineering

The model should focus on the gesture and be invariant to the person's position relative to the camera.

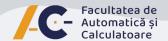
=> Extract features relative to the person from the landmarks.





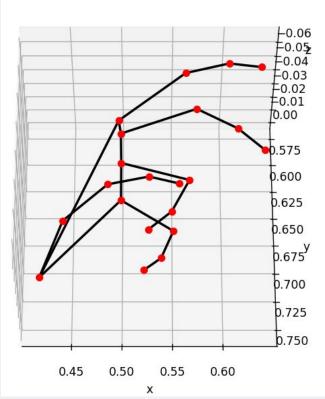
2.1. World Landmarks

- MediaPipe also extract "World Landmarks"
- For MediaPipe Hands, they are the distance in meters from the hand's center.
- For *MediaPipe Pose*, they are the distance in meters from the hips' center.





Landmarks



World landmarks

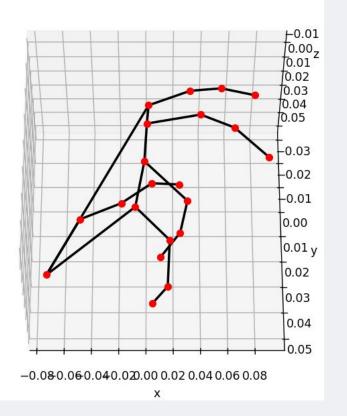


Fig. 10: High-Level Overview of the Backend.





2.2. Movement Direction

- Problem: World Landmarks lose information regarding the movement's direction.
- **Solution:** compute and normalize the difference in position between corresponding landmarks in consecutive frames.

2.3. Joint Rotations

The rotations to align the model to the landmarks.





3. Gestures Classifier

- 3 LSTM layers followed by 3 dense layers.
- Recurrent dropout after every LSTM layer to prevent overfitting.
- Activation function: ReLU for hidden layers and Softmax for output layer.
- Loss function: Categorical cross-entropy.
- Optimizer: Adam
- Callbacks: LR scheduler, early stopping and model checkpoint.

```
gestures_model = Sequential([
      LSTM(64, return_sequences=True, activation='relu',
           input_shape=(X.shape[1], X.shape[2]), recurrent_dropout=0.2),
      BatchNormalization(),
      LSTM(128, return_sequences=True,
           activation='relu', recurrent dropout=0.2),
      BatchNormalization(),
      LSTM(64, return_sequences=False,
           activation='relu', recurrent_dropout=0.2),
      BatchNormalization(),
     Dense (64, activation='relu'),
      BatchNormalization(),
     Dense (32, activation='relu'),
      BatchNormalization(),
      Dense(y.shape[-1], activation='softmax')
16 ])
18 gestures model.compile(
      optimizer=Adam(learning rate=0.001),
      loss='categorical_crossentropy',
      metrics=['categorical_accuracy']
 Snippet 1: Gestures Classifier Architecture.
```





4. ChatGPT API Service

- Builds a coherent sentence from the given words.
- Passes a list of predicted words to ChatGPT along with the conversation history and a system message.
 - The history provides context for better sentence building.
 - The system message explains the task and gives examples for few shot learning.





Conclusions

1. Main Results

- Can translate:
 - over 4000 words from RO to RSL
 - 60 gestured RSL signs into RO
- Application is performant enough to run on mid-range Android devices.
- Gestures classifier achieves on the test dataset:
 - o 100% accuracy
 - 99.89% confidence
- Animated gestures were found to be understandable by an interpreter.

2. Future Work

- Use updated MediaPipe Holistic version once available.
- Larger, improved and more varied dataset created by recording an expert.
- Implement a sign language segmentation algorithm and not rely on heuristics.







Conclusions

3. Summary of contributions

- Created RSL vocabulary from scraped and processed videos.
- Applied Kalman and moving average filters to correct and smooth data.
- Used inverse kinematics to create animations.
- Created a service using NLP and various metrics to match natural speech with vocabulary entries.
- Created a RSL dataset recording pipeline which was used to create the dataset necessary for training a custom gestures classifier.
- Derived representative and robust features as the model's input.
- Developed a service interfacing with ChatGPT to form coherent sentences from predicted words.
- Bundled all functionalities into an Android app for portable, real-time, bidirectional translation.

Thank You! <<<<