

Detailed Flowchart

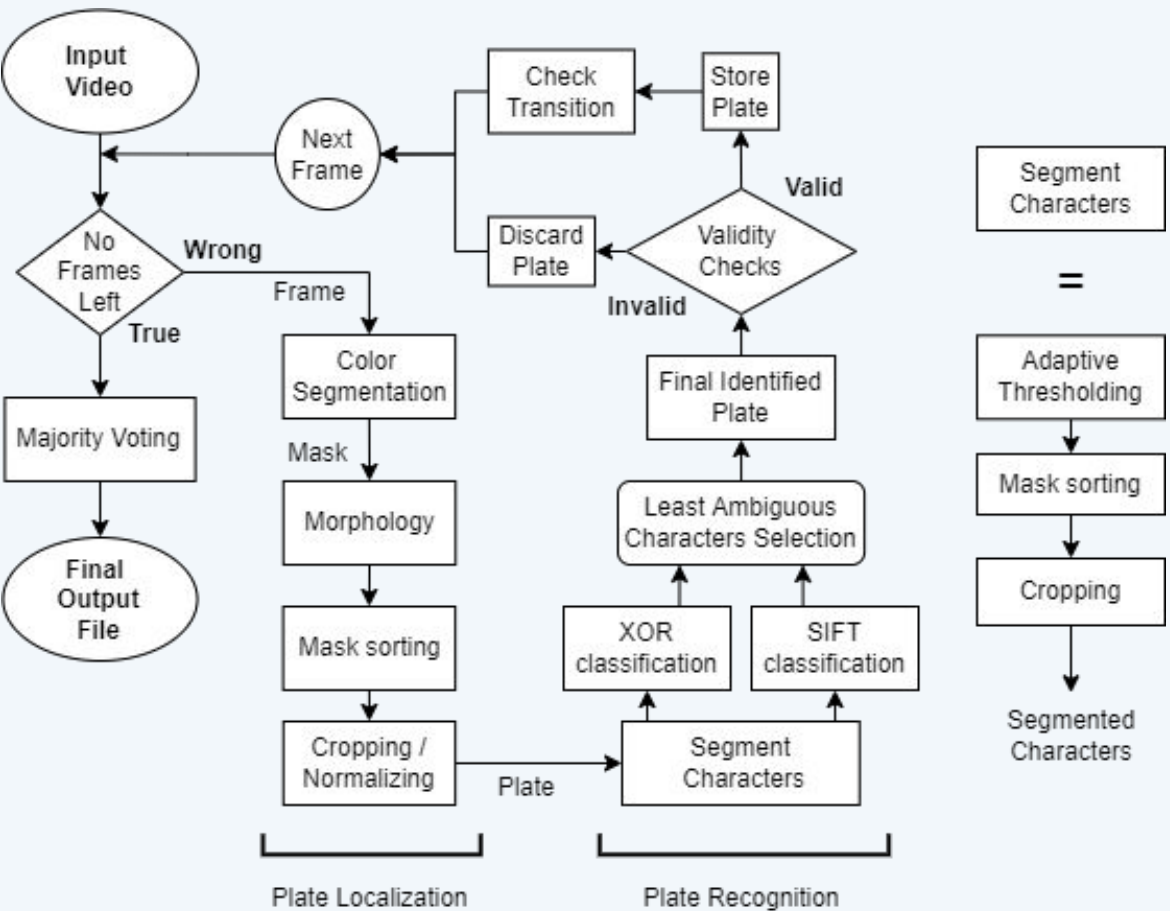
The input video is sampled into individual frames, out of which we extract plates through a repeat process detailed here:

We firstly obtain a mask on the frame with color masking and morphology; Sort its components based on bounding boxes, contours and areas, in order to then segment, crop and rotate the plate.

We then use adaptive thresholding to segment the individual digits from the plate, which we then classify using two 2-nn algorithms (SIFT descriptors distances, pixel-wise XOR distances) against a reference characters database. We form the predicted plate number by picking, for each character, the guess from the party with least ambiguity.

Finally, if the prediction isn't aberrant, store it and possibly a transition if it's unsimilar to the previous predictions.

In parallel, we compile a list of one predictions per plate, based on majority voting; once every frame is analyzed, return it along with timestamps and frame numbers in the output file and we're done.



Evaluation on the Training Video

The evaluation of the pipeline on the training video yields the following results.

Notice that our pipeline has been designed with a goal of reaching satisfying results in category I and II, which yield a combined score of 92%:

| | FN | FP | TP and Score |
|-----|----|----|----------------|
| I | 2 | 1 | 27 / 30 = 90% |
| II | 0 | 0 | 10 / 10 = 100% |
| III | 5 | 2 | 3 / 10 = 30% |
| IV | 10 | 0 | 0 / 10 = 0% |

Edge Cases and aberrations

We detect edge cases with a measure of ambiguity from our two classifiers; Which we define as the ratio of the best match over the second best one.

To avoid ambiguities, we simply pick the guess from the classifier that presents the least ambiguity.

Regarding aberrations, the pipeline simply dismisses them. Since the plates have many different frames in which they can be detected, we do not go through the trouble to try to correct aberrant predictions. Instead, we simply skip further analysis and discard them.

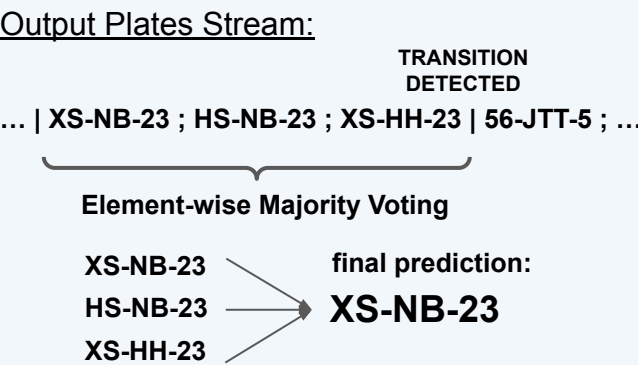
Transition to a new Scene / Plate

- A transition is considered when:
- The current plate and the previous one have at least 4 differences.
 - There's been at least 24 frames since the last transition.
 - The sets of characters constituting the current and previous plate differ by at least 2 elements.
- A transition however only is registered if the next plate to be recognized, is also conflicting with the previous plate in the same way as the current plate.
- This way we require two distincts cases of dissimilarity to detect a transition.

Merging / Voting system

Whenever a transition has been detected, we look back at the previously stored plates, that all correspond to the same vehicle, in order to merge them into one final prediction to put on the output file.

For each character of the final prediction, we simply choose the most occurring character from the batch we stored.



Conclusions and Improvements for weaknesses

As can be seen on our flowchart, our pipeline is essentially pretty simple, only making use of few repeated algorithms. And while we did implement additional features, such as image filtering and edge detection, we ended up leaving them aside without further experimentation. While simplicity is computationally advantageous, one could argue that the system ends up being somewhat naive and underperforming, for category III and IV.

A first step for improvement would be to enable detection of several plates in one frame instead of aiming at only finding one. Most importantly however, the pipeline should be able to localize the plates without relying on color masking but rather on the plates' shape with some edge detection; In order to also be able to generalize the system to international license plates detection.