Automatic Text Identification, Recognition and Physical Address Generation from Unstructured Video

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Outline

Importance of Topic

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  - Track a video on a map and add informations on to the map from extracted information.

Dataset

- A 38 second video (16fps).

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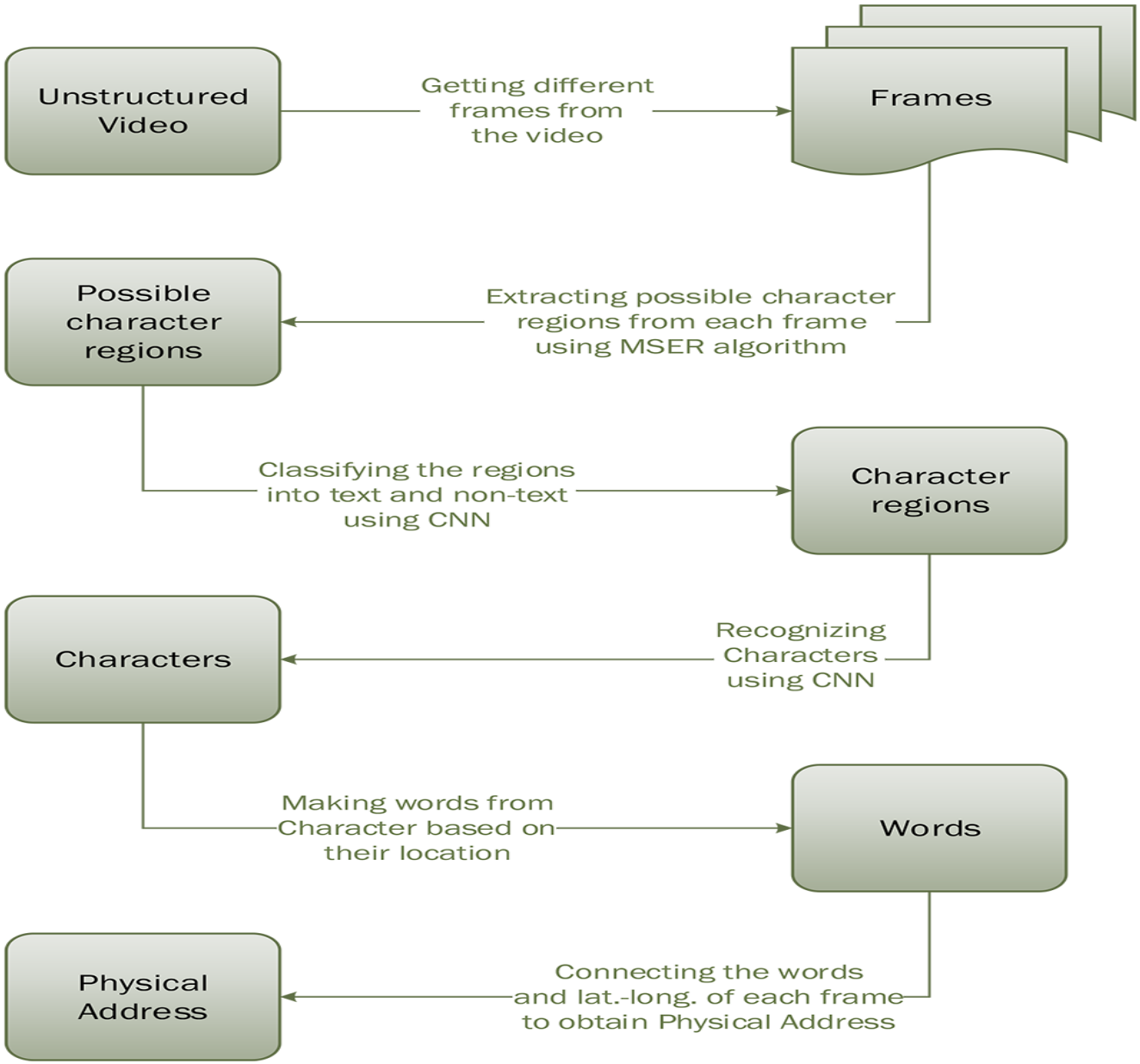
- A 38 second video (16fps).
- Latitude and longitude of camera for each second.

Work-flow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Connecting the words and lat.-long. of each frame to obtain Physical Address

Edge based Text Extraction

- Initial Frame

Edge based Text Extraction

- Text regions identified

Edge based Text Extraction

- Same method failed for few other frames:

Figure 1: Initial Image

Edge based Text Extraction

- Same method failed for few other frames:

Figure 1: Initial Image

Figure 2: Final Image

Edge based Text Extraction

- Same method failed for few other frames:

Figure 3: Initial Image

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Figure 3: Initial Image

Figure 4: Final Image

New Approach

- Super-pixel segmentation.

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- Quick shift image segmentation.

New Approach

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- Quick shift image segmentation.
- Finally:
  - Maximally stable extremal regions - MSERs [4]

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- MSER algorithm extracts stable regions from an image by considering the change in area with respect to the change in intensity of a connected component defined by thresholding the image at different gray levels.

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- Why MSER?
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  - *Stability*: Only regions whose support is nearly the same over a range of thresholds is selected.
  - *Multi-scale* detection, both fine and large structure is detected.

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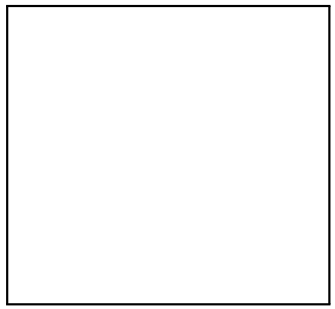
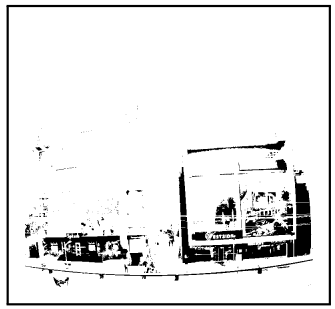
  - All the pixels above a given threshold are white and all those below or equal are black.
  - If we are shown a sequence of thresholded images I_t with t corresponding to threshold t, we would see first a white image, then black spots starts appearing then grow larger. These will eventually merge, until the whole image is black.

Maximally stable extremal regions (MSERs)


(a) Initial


(b) t = 10


(c) t = 50


(d) t = 60


(e) t = 80


(f) t = 70


(g) t = 90


(h) t = 100

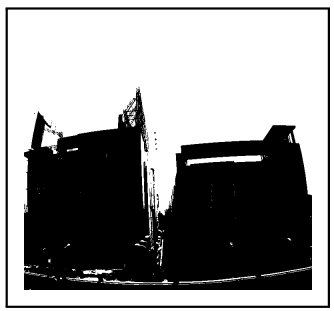

(i) t = 110


(j) t = 120

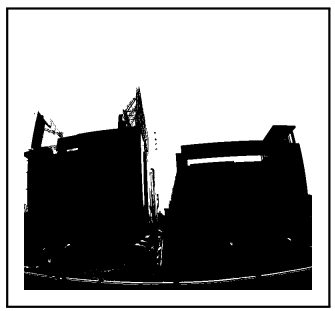

(k) t = 130


(l) t = 140

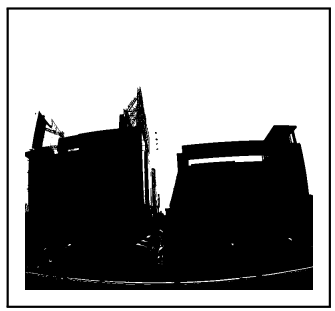
Maximally stable extremal regions (MSERs)



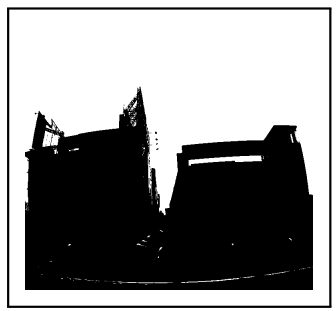
(m) t = 150



(n) t = 160

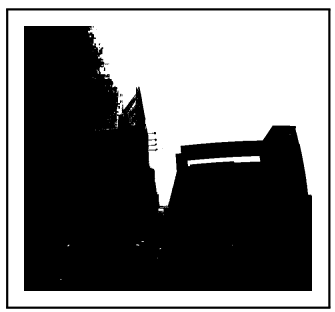


(o) t = 170



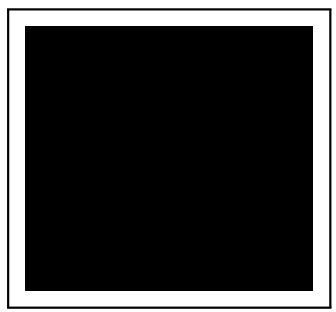
(p) t = 180

(q) t = 190



(r) t = 200

(s) t = 220



(t) t = 255

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- In extremal regions, pixel values are either strictly darker or strictly brighter than those on the boundary.
- A region is considered stable if its area changes only slightly with the change of threshold t.

MSERs - Algorithm [4]

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- The list of connected components and their areas is tracked using the efficient union-find algorithm. (Order: nlog(log(n)))
- The process produces a data structure storing the area of each connected component as a function of intensity.
- Finally, intensity levels that are local minima of the rate of change of the area function are selected as thresholds producing maximally stable extremal regions.

MSERs - Observations

- MSER applied on simple images (ICDAR[1] 2015 dataset)

[1] ICDAR 2015. "Incidental Scene Text Dataset". In: *International Conference on Document Analysis and Recognition* (2015).

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Figure 5: MSERs initially identified on ICDAR[1] 2015 image

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MSERs - Observations

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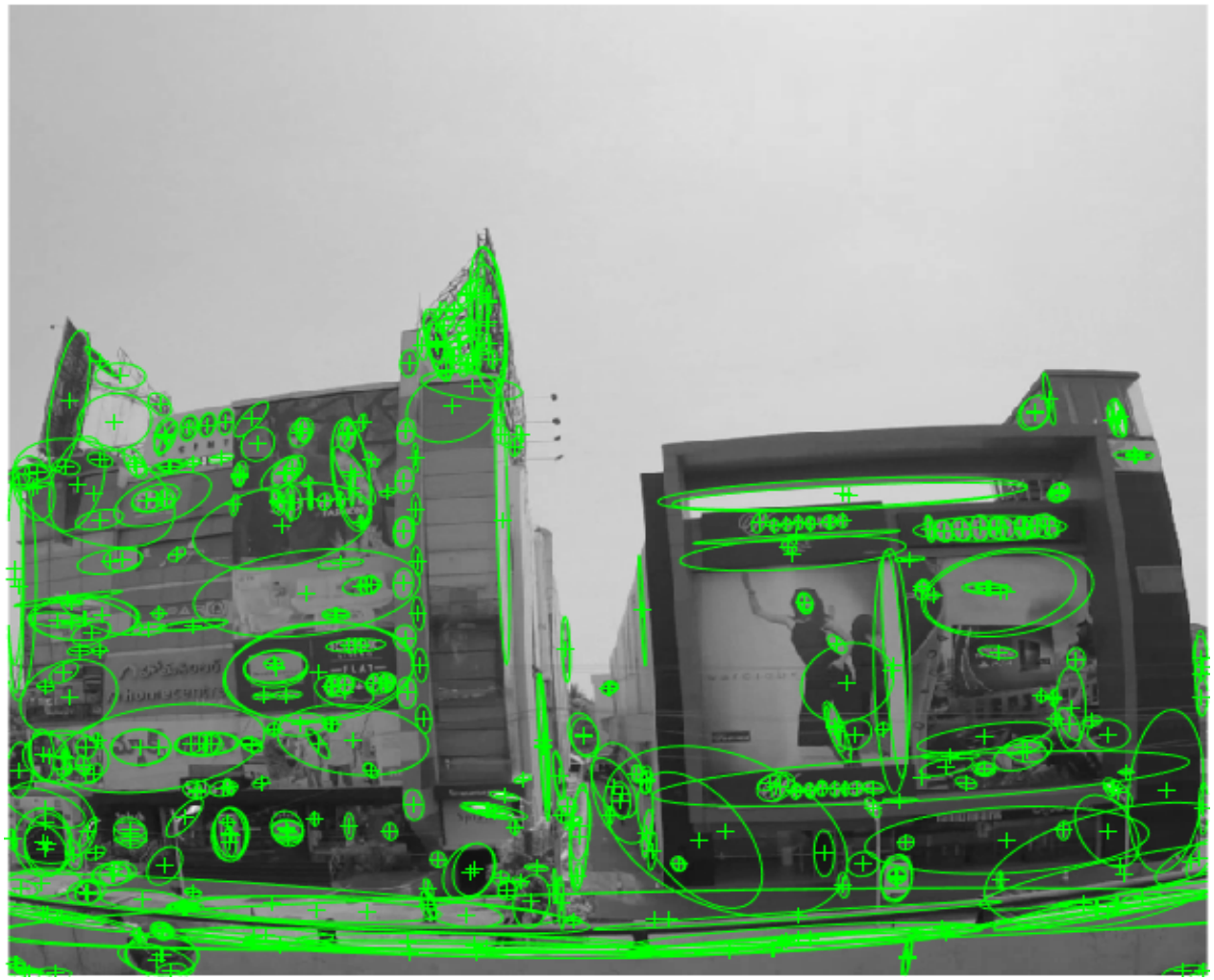


Figure 6: MSERs initially identified on video frame

MSERs - Observations

- MSER applied on video frames

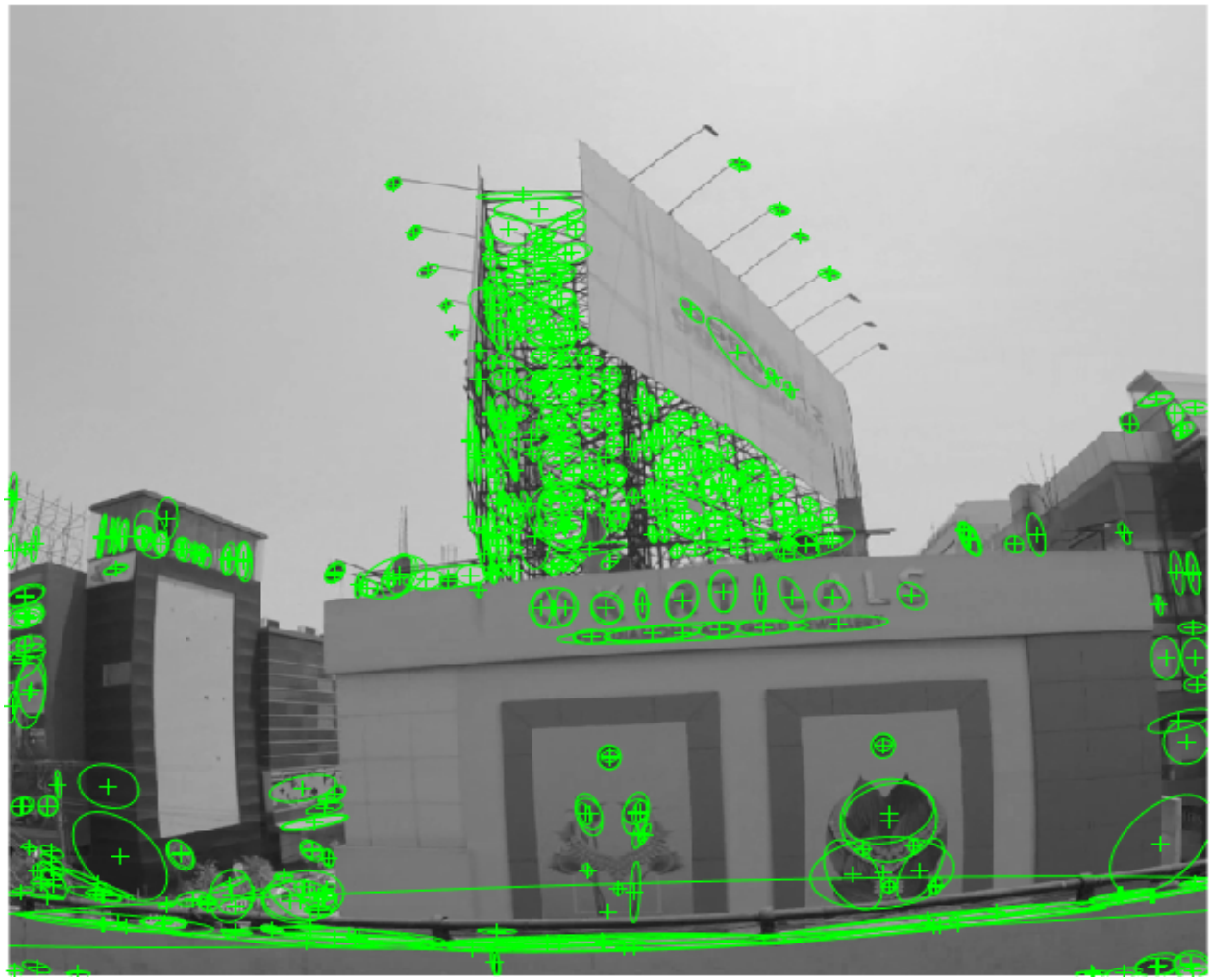
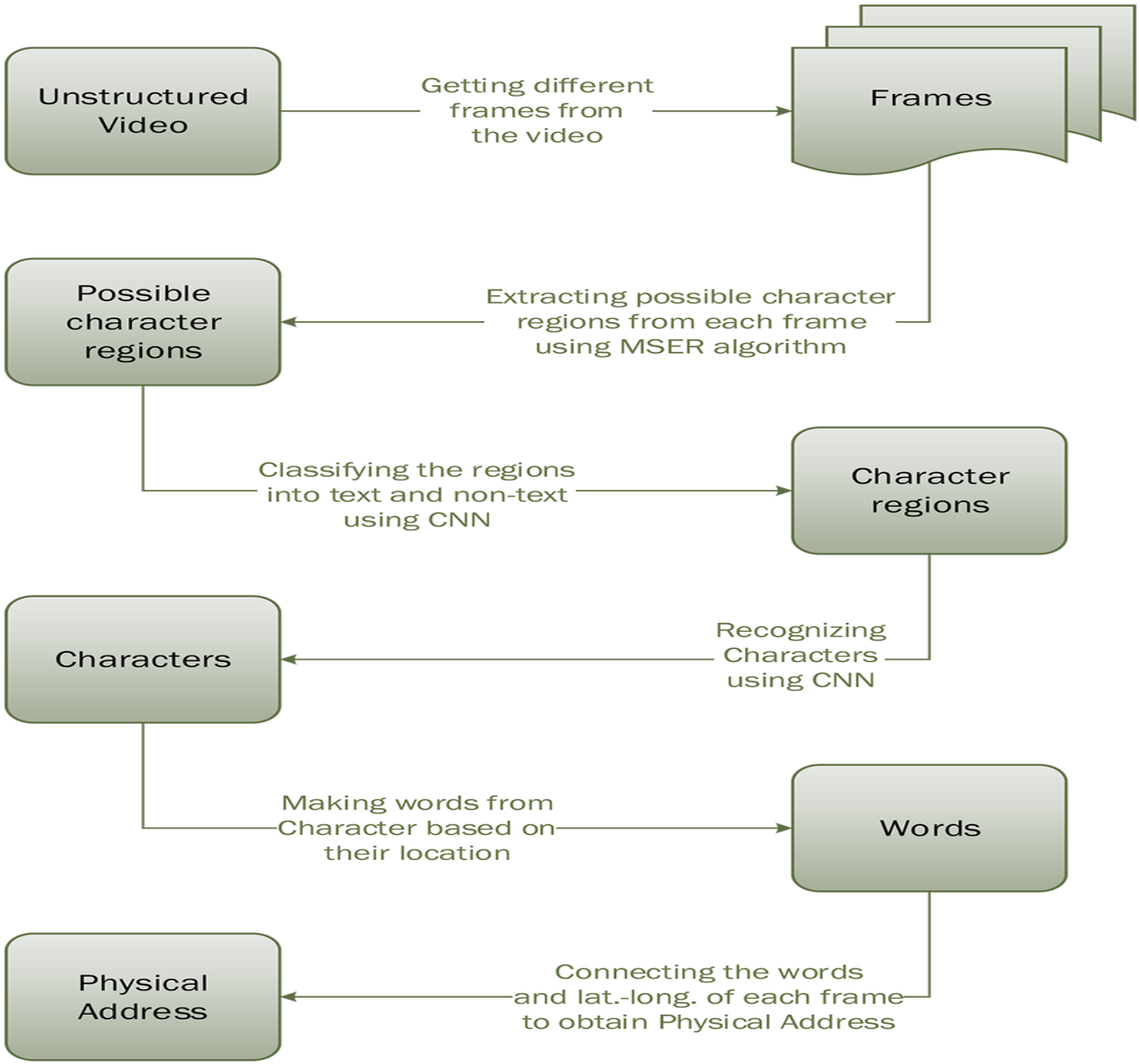


Figure 7: MSERs initially identified on video frame

Work-flow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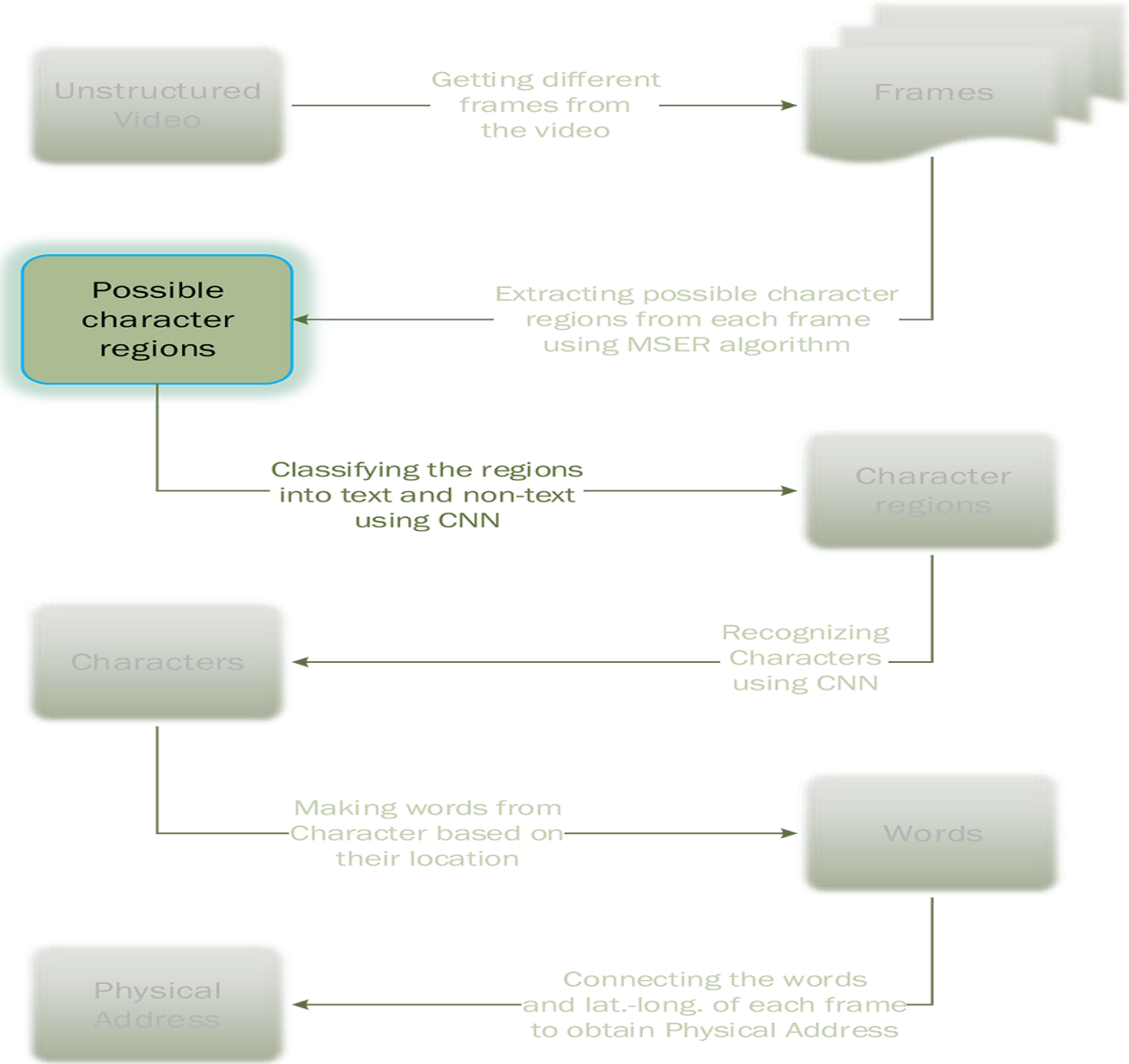
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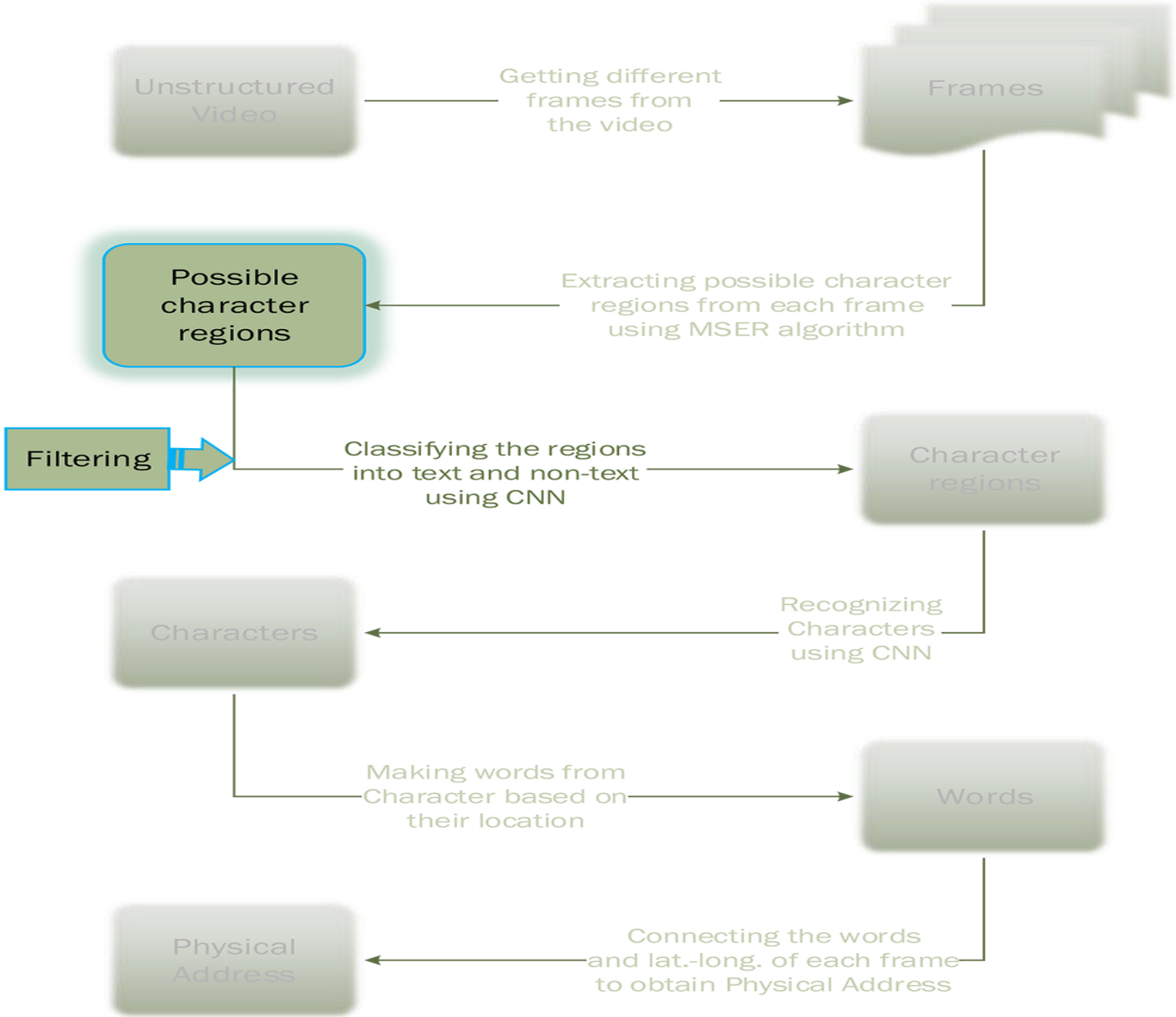
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MSERs - Initial Filtering

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- There are regions in which the width by height ratio is very high, these can also be removed by keeping a threshold on width by height ratio.

MSERs - Observations

- After initial filtering

Figure 8: Filtered MSERs on ICDAR 2015 image

MSERs - Observations

- After initial filtering

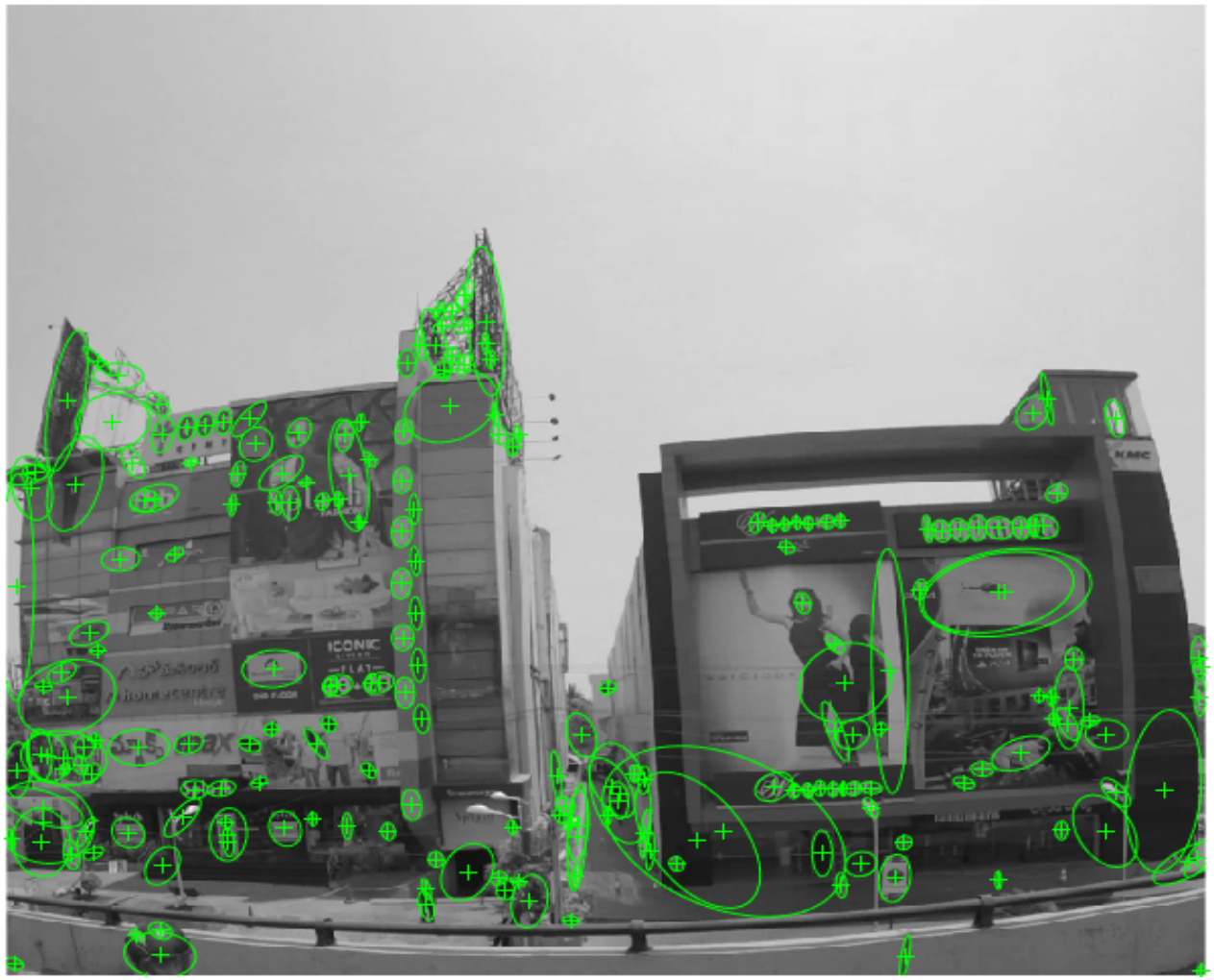

Figure 9: Filtered MSERs on video frame

MSERs - Observations

- After initial filtering

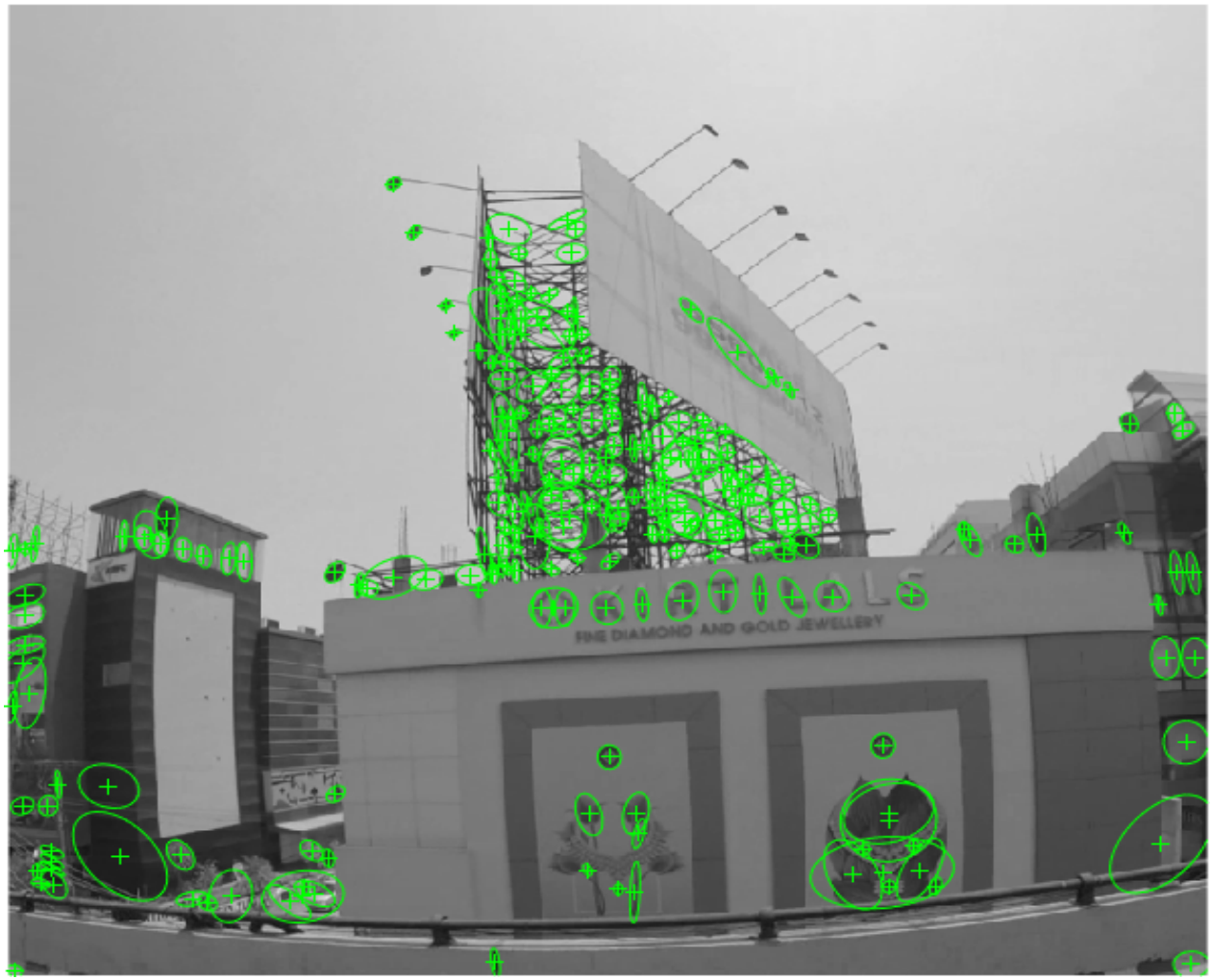

Figure 10: MSERs initially identified on video frame

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  - Soft-max layer.

Classification - Observations

- Text and Non-Text classification applied on simple images

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Figure 11: Classified Text regions on ICDAR 2015 image

Classification - Observations

- Text and Non-Text classification applied on video frames

Classification - Observations

- Text and Non-Text classification applied on video frames

Figure 12: Classified Text regions on video frame

Classification - Observations

- Text and Non-Text classification applied on video frames

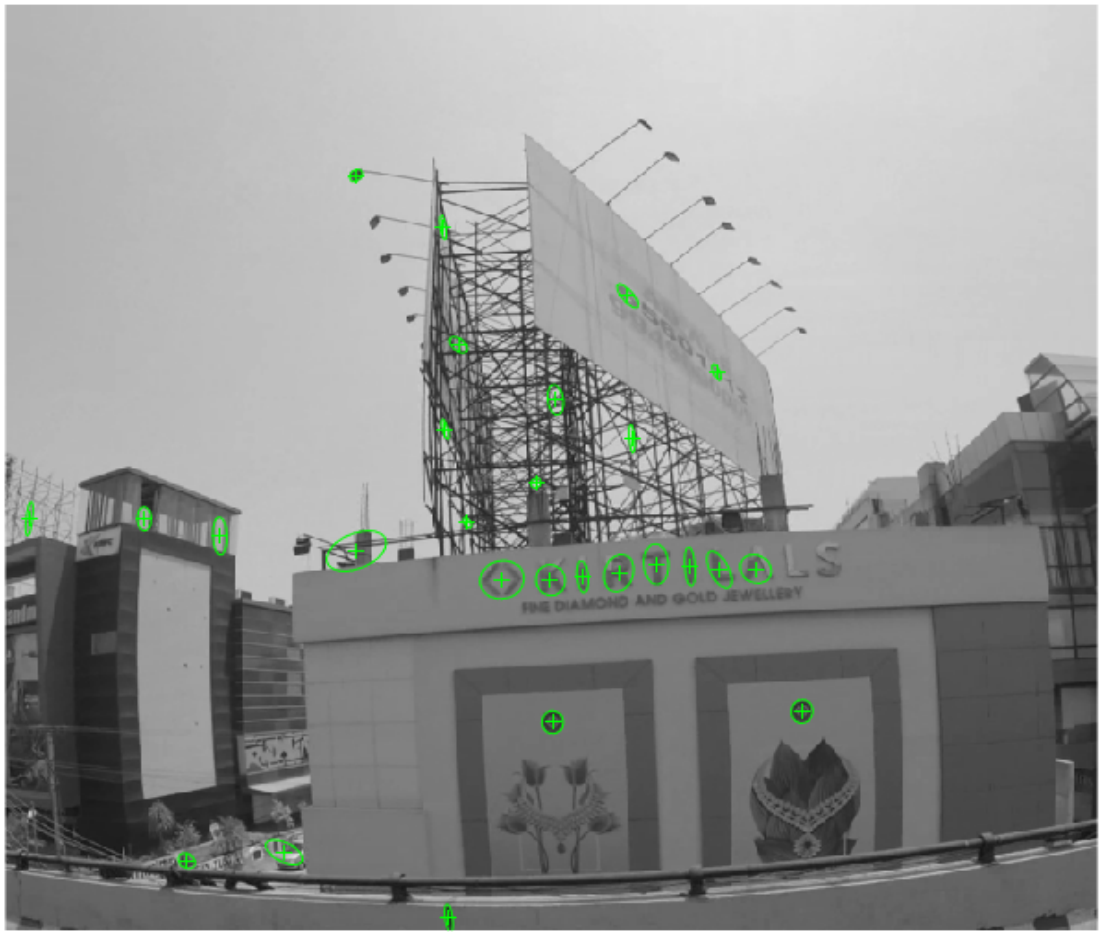
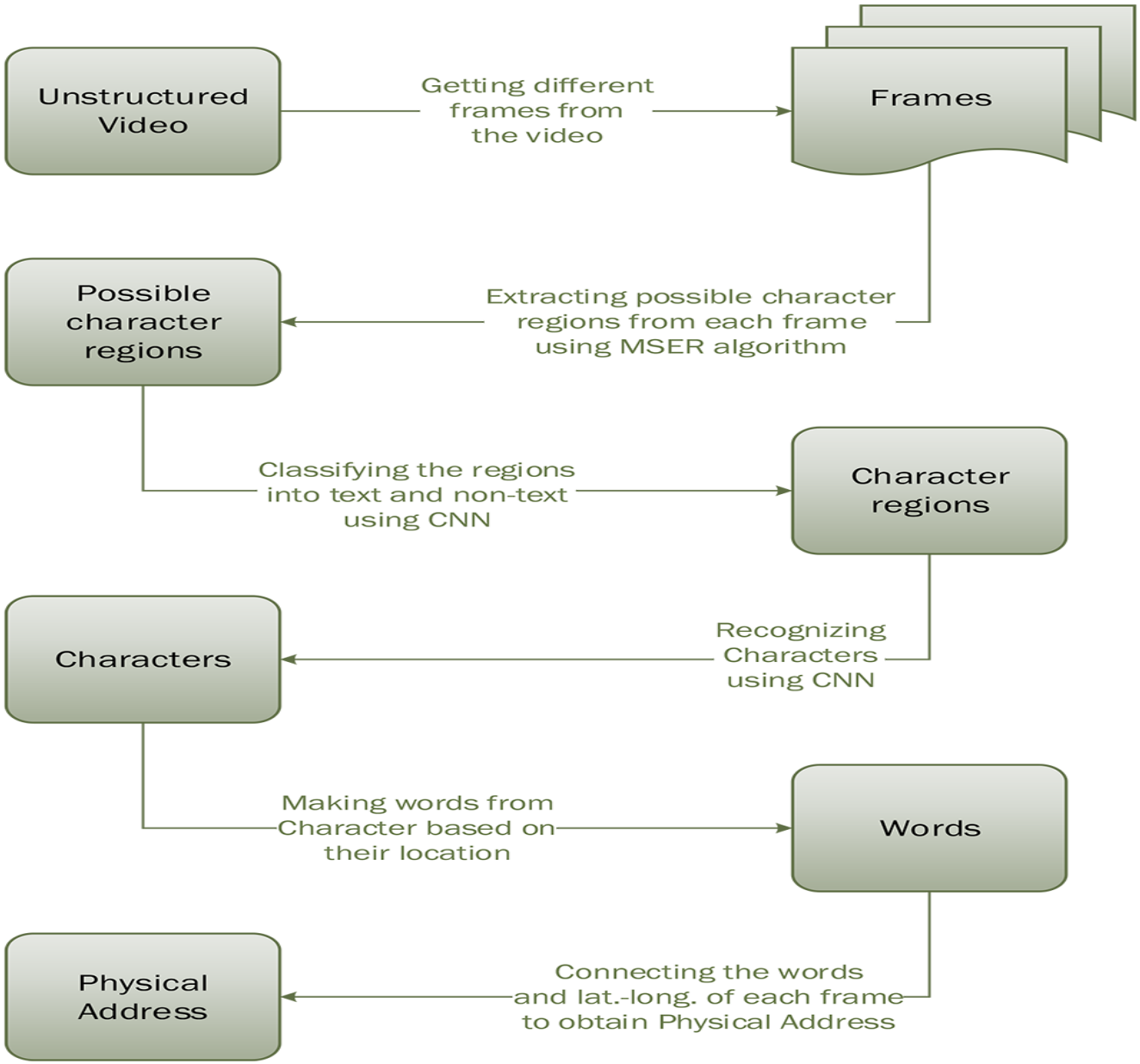


Figure 13: Classified Text regions on video frame

Work-flow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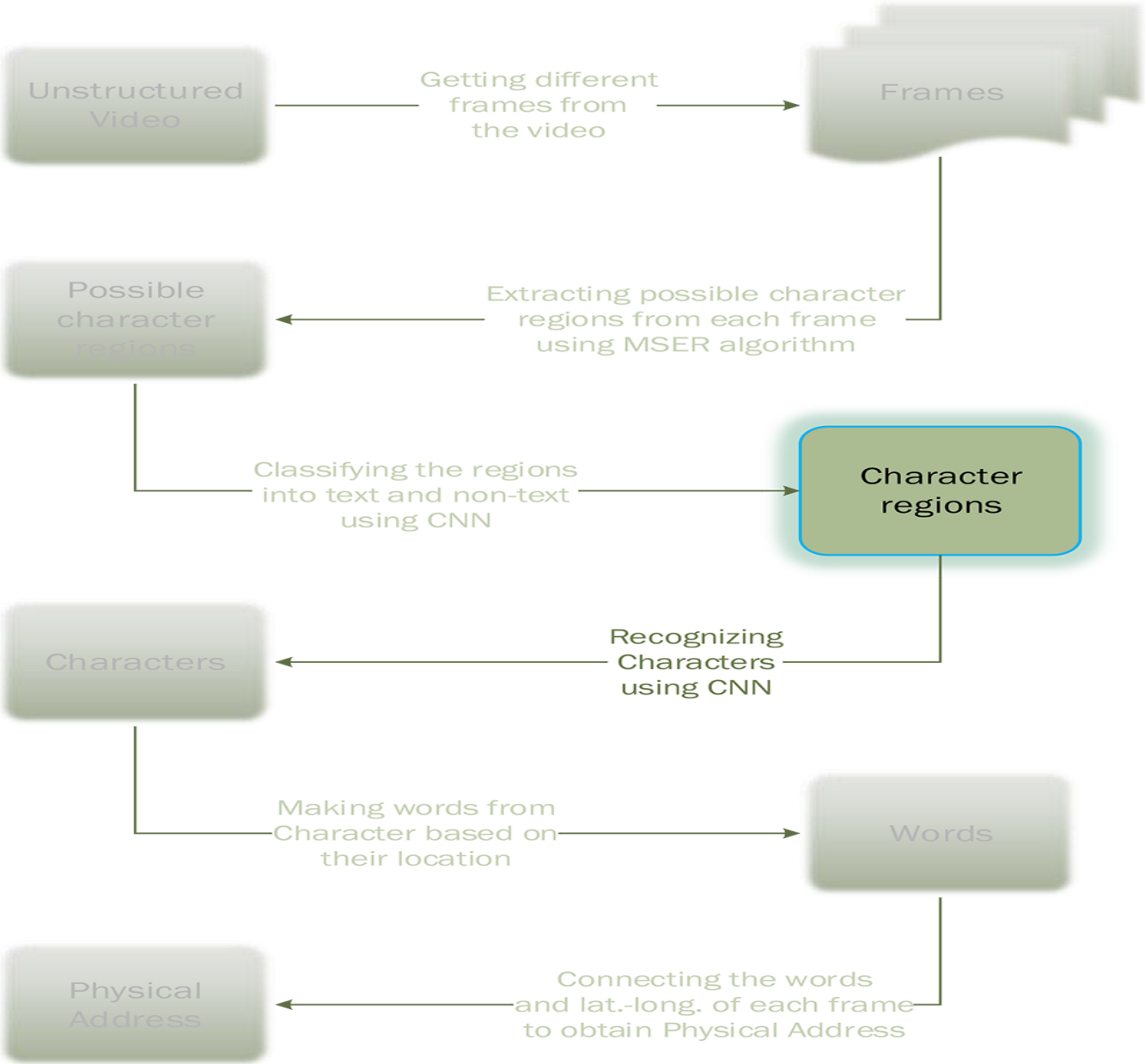
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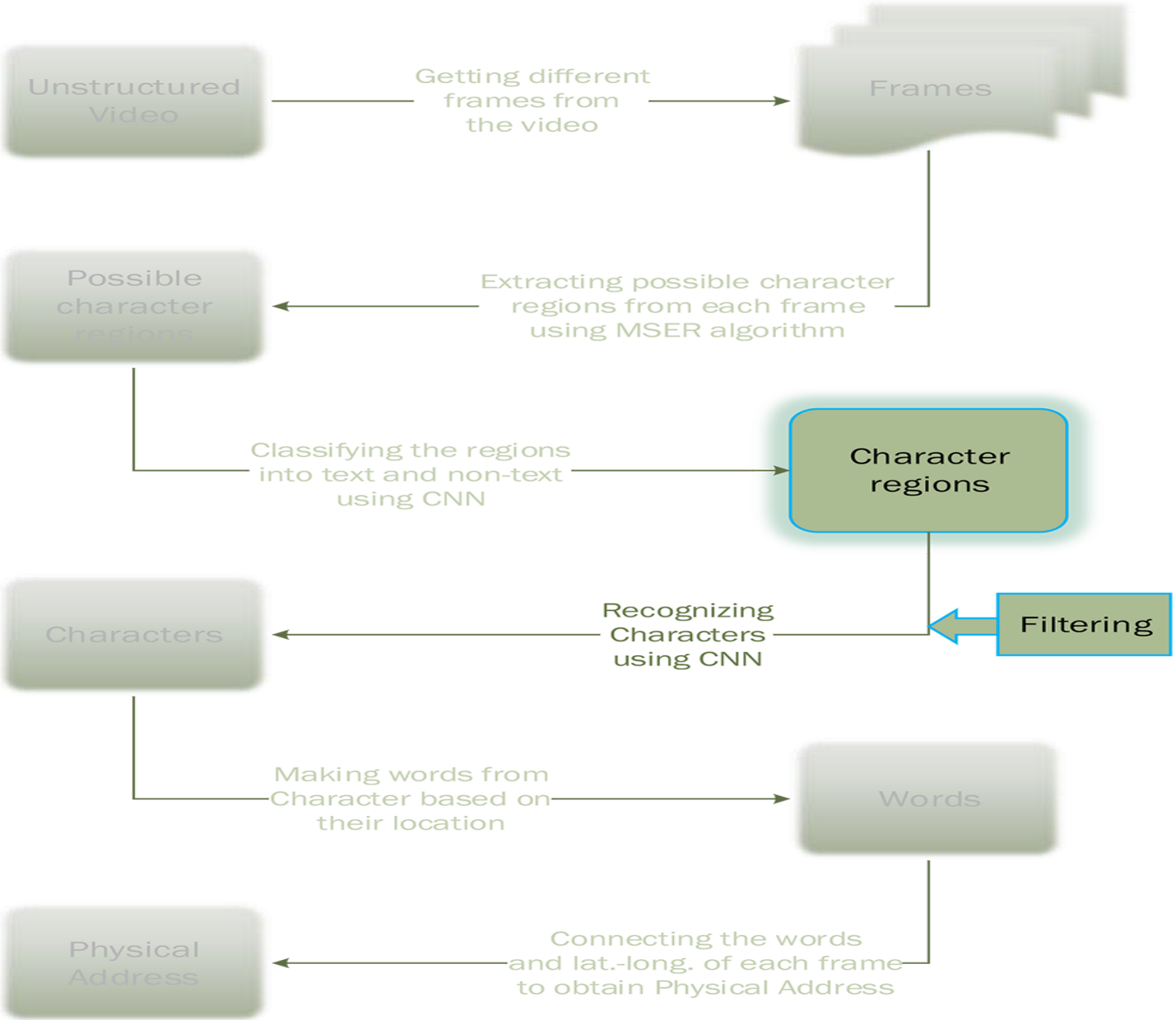
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- Regions classified as Text should occur with a uniform distance between the characters and at-least 2 together (we are assuming that there will not be any word in the image with only one character).

Classification - Initial Filtering

- After Text and Non-Text classification, there are still some false positives.
- Regions classified as Text should occur with a uniform distance between the characters and at-least 2 together (we are assuming that there will not be any word in the image with only one character).
- After applying this filter based on distance between the center of regions, we are left with just text regions.

Classification - Observations

- Filtering applied on classified Text regions

Classification - Observations

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Figure 14: ICDAR Images

Classification - Observations

- Filtering applied on classified Text regions

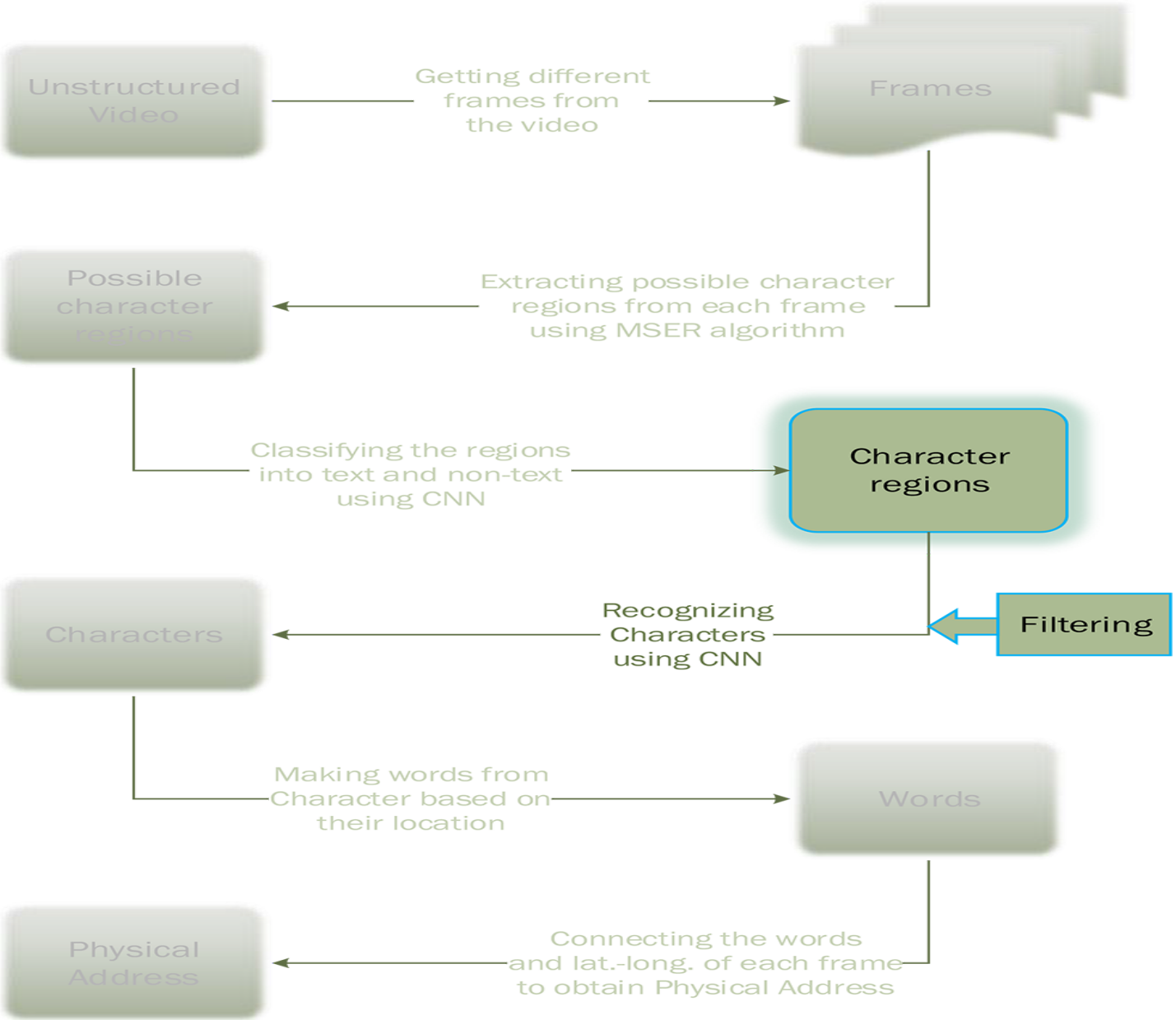
Figure 15: Video frames

Classification - Observations

- Filtering applied on classified Text regions

Figure 16: Video frames

Work-flow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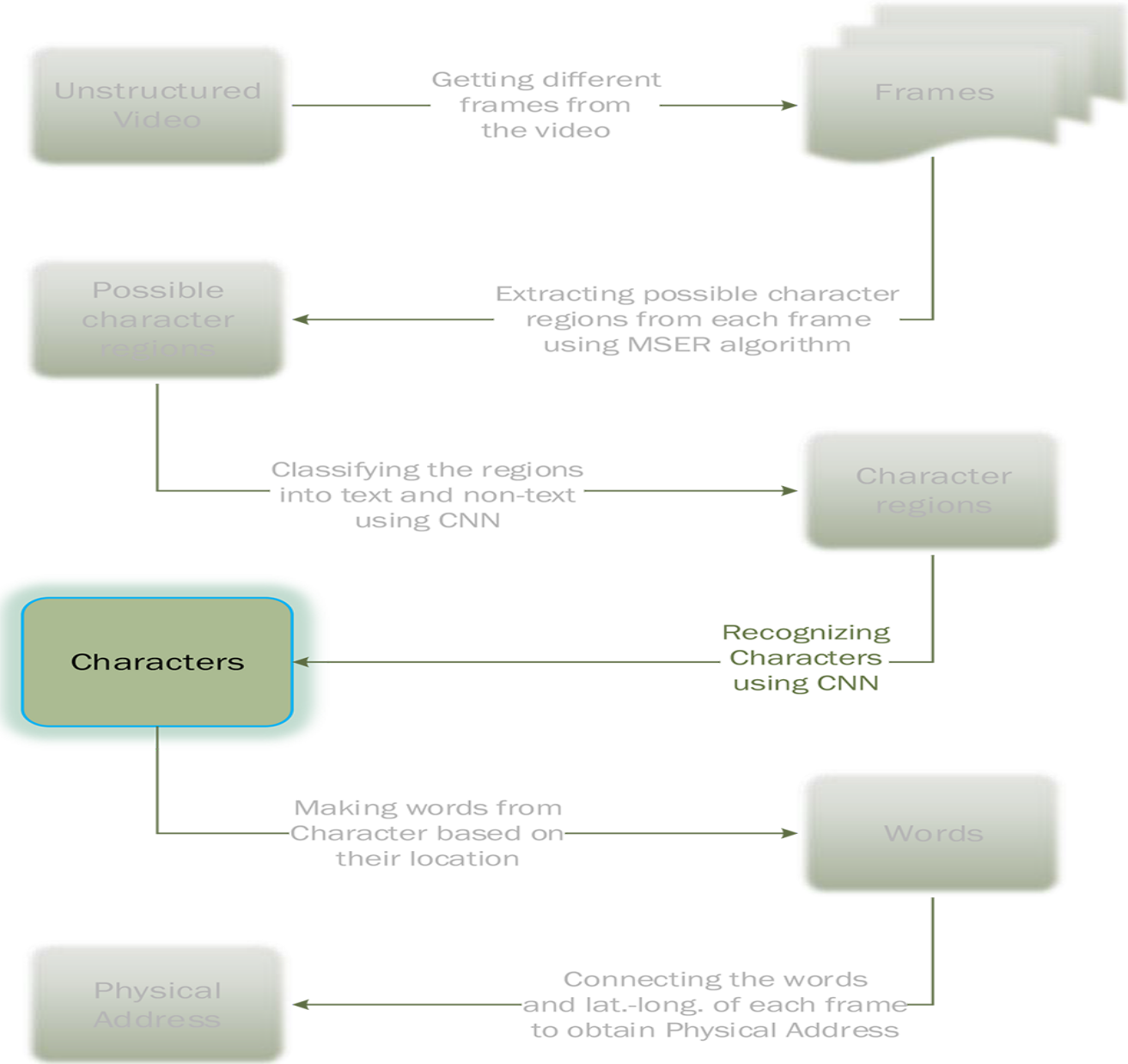
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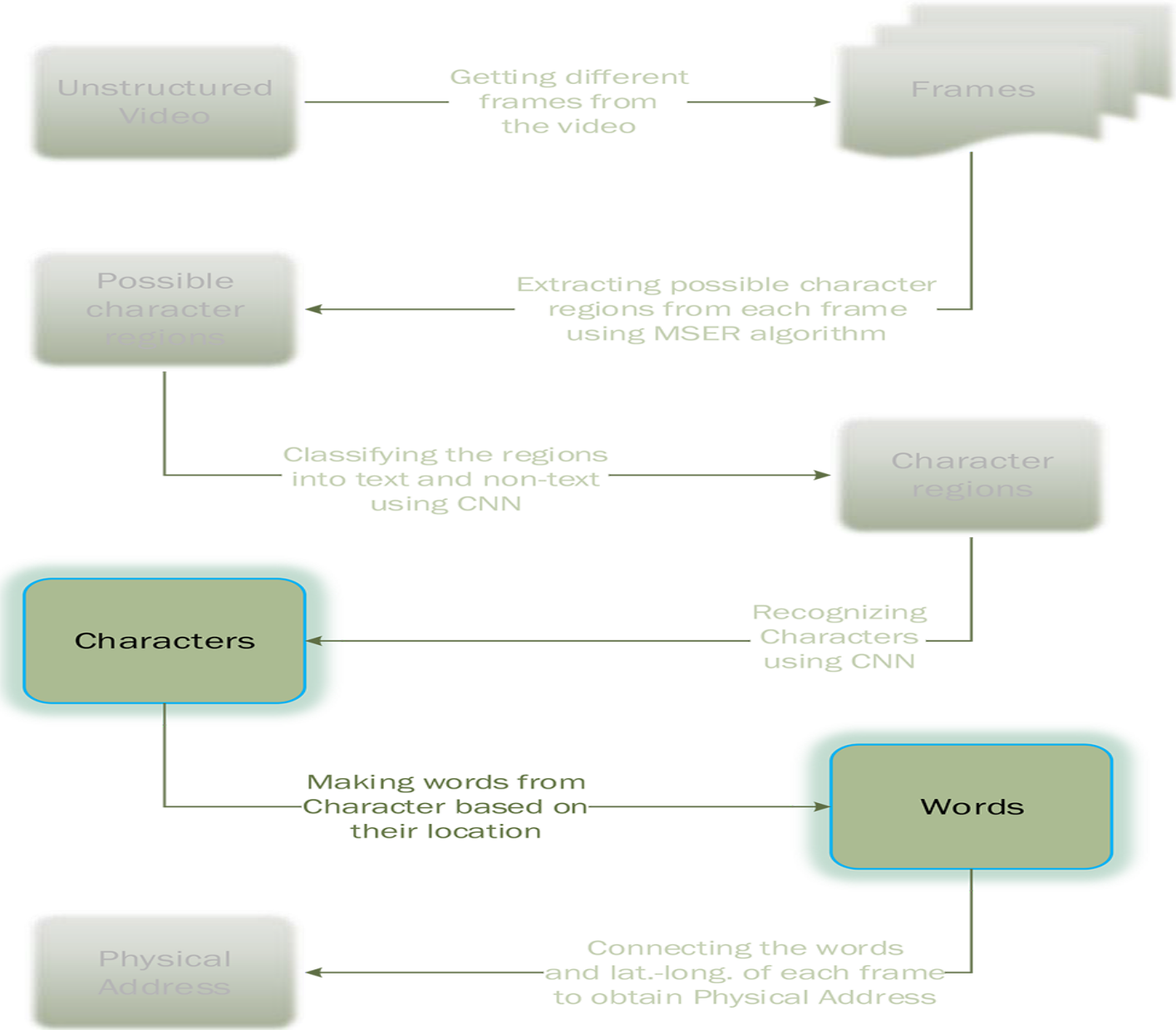
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Text Recognition - Observations

- Recognized texts on simple images

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Figure 17: ICDAR Images

Text Recognition - Observations

- Recognized texts on video frames

Text Recognition - Observations

- Recognized texts on video frames

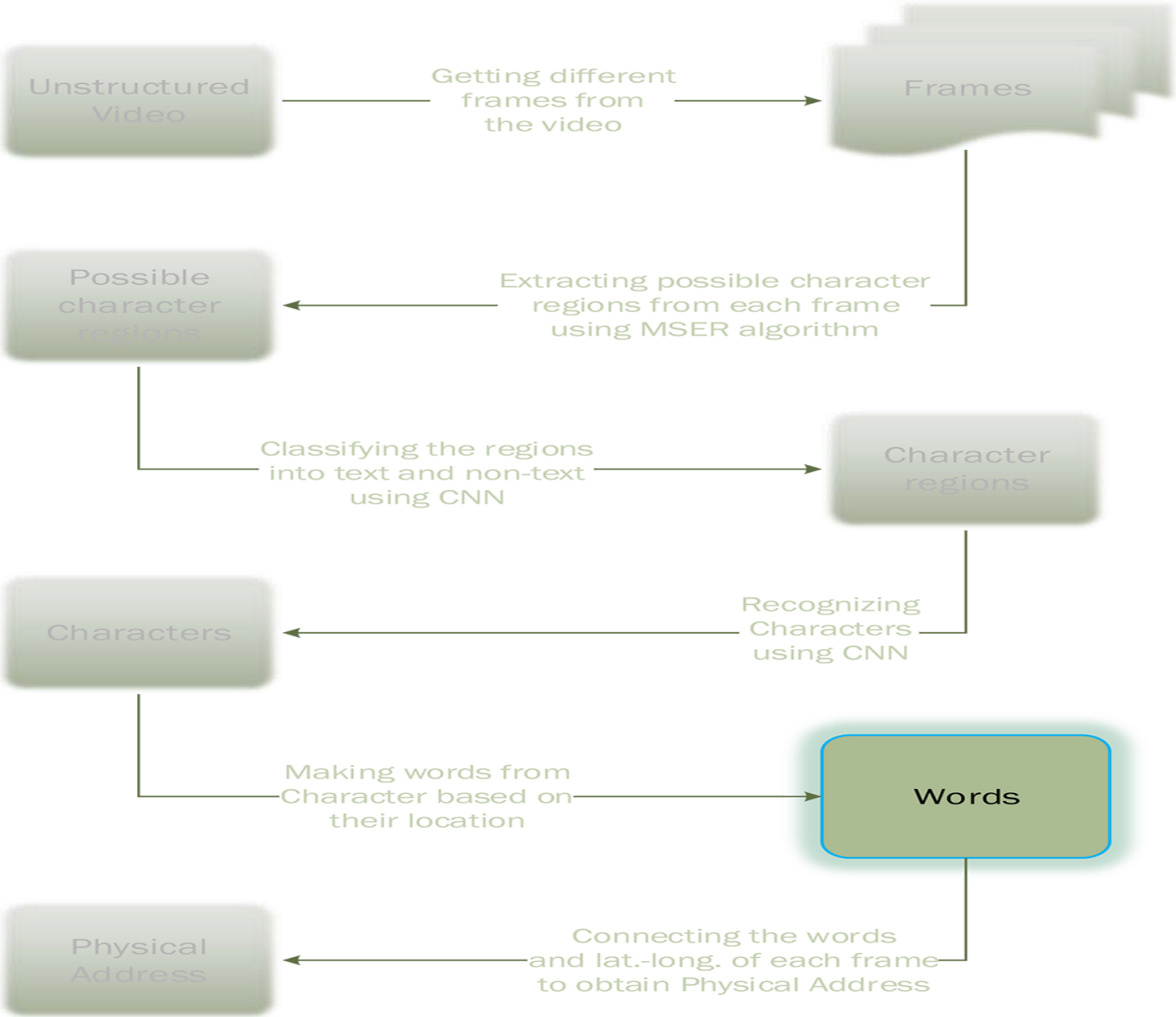
Figure 18: Video frames

Text Recognition - Observations

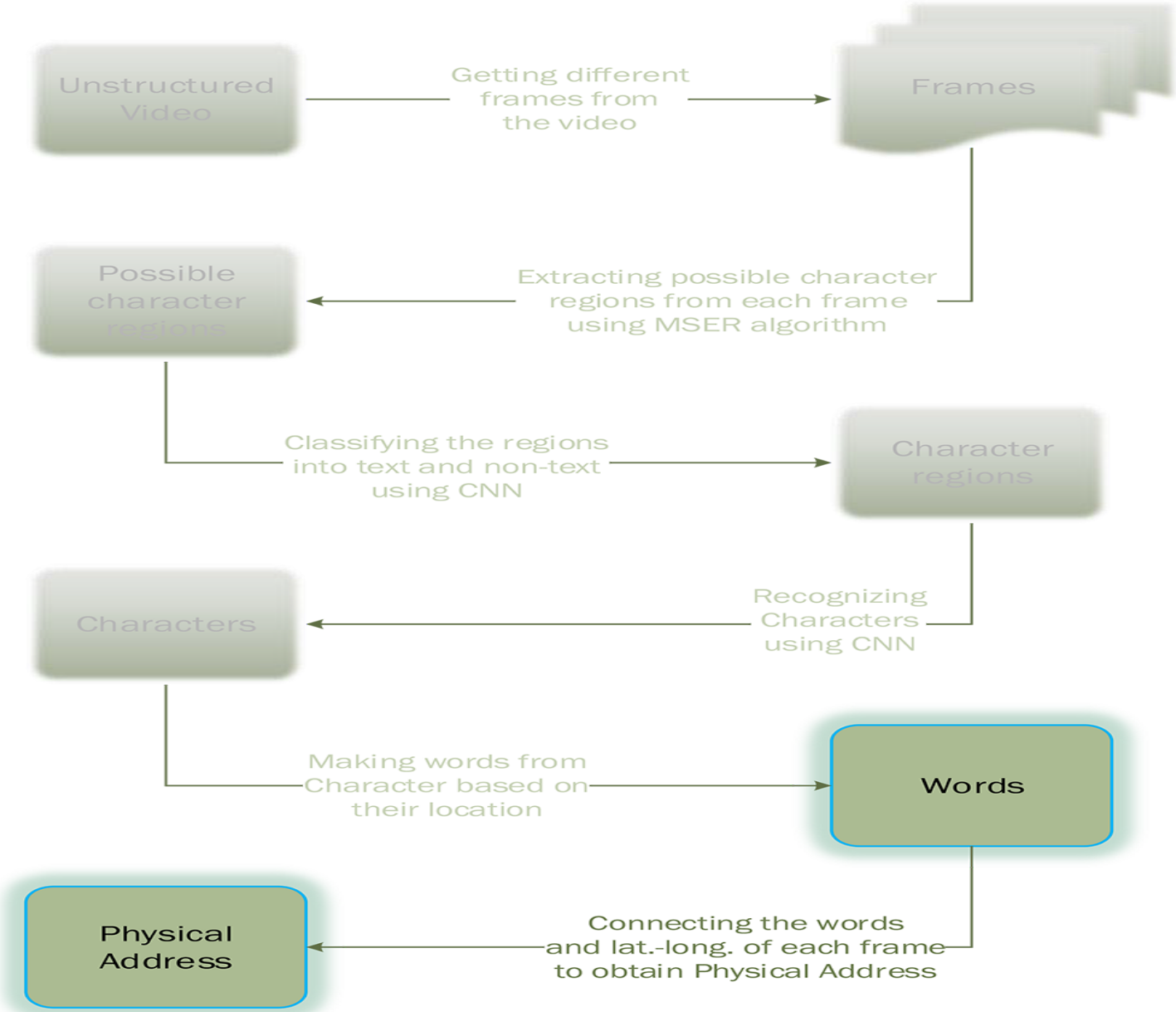
- Recognized texts on video frames

Figure 19: Video frames

Work-flow


Unstructured Video
Getting different frames from the video
Frames
Possible character regions
Extracting possible character regions from each frame using MSER algorithm
Classifying the regions into text and non-text using CNN
Character regions
Characters
Recognizing Characters using CNN
Making words from Character based on their location
Words
Physical Address
Connecting the words and lat.-long. of each frame to obtain Physical Address

Work-flow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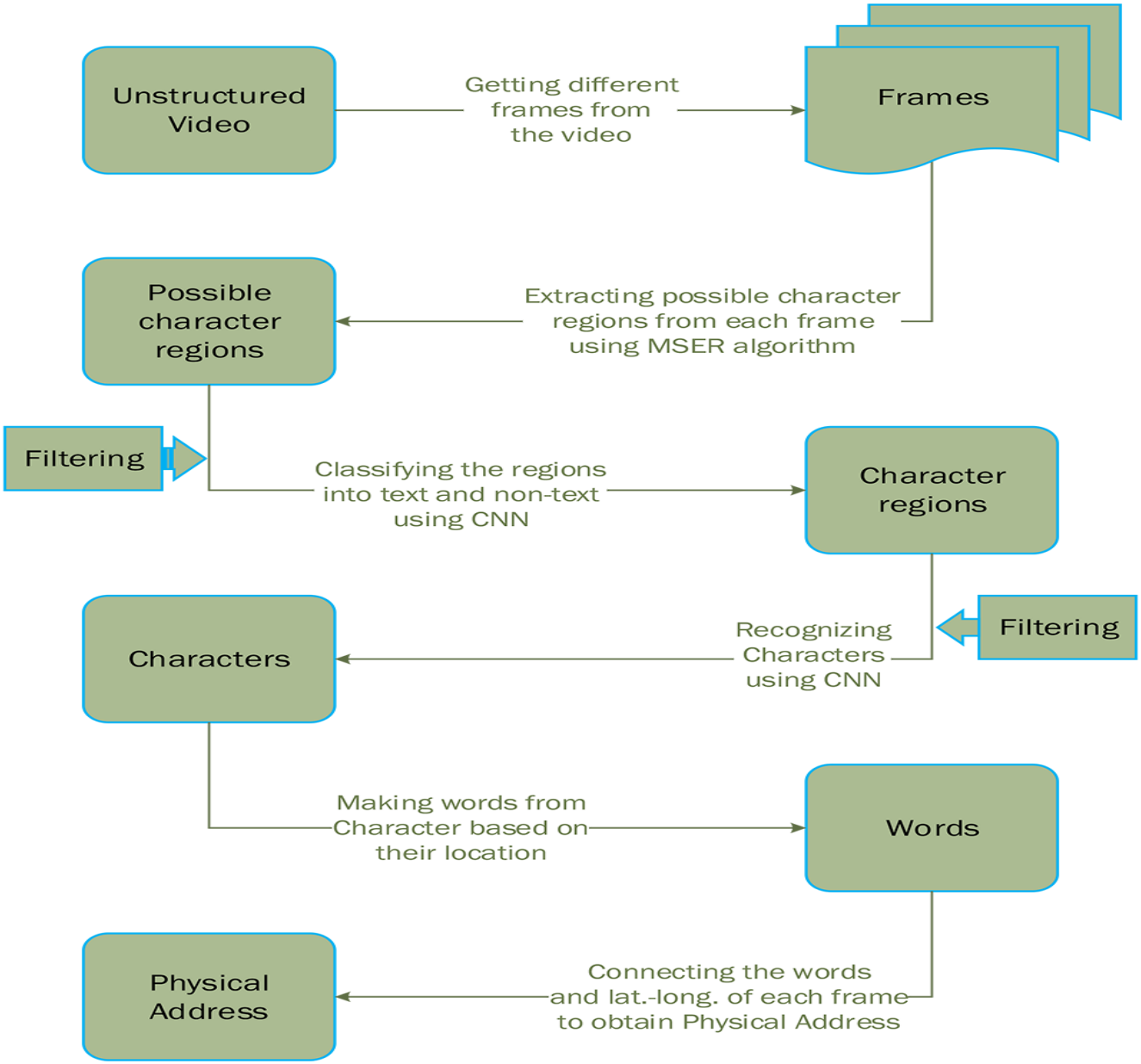
- Possible Reason:
  - Images not well focused and are with very less quality.
- Recommendations:
  - Use **extremal regions** instead of **MSERs** (Computationally very expensive).
  - Use of well tuned classifier (CNN configuration tuned and trained for this specific dataset).

Summary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References

[1] ICDAR 2015. "Incidental Scene Text Dataset". In: *International Conference on Document Analysis and Recognition* (2015).

[2] I. Sutskever A. Krizhevsky and G. E. Hinton. "ImageNet classification with deep convolutional neural network". In: *Proc. Conference on Neural Information Processing Systems* (2012), pp. 1097–1105.

[3] Larry Brown. *Using cuDNN depth neural network*. 2014. URL: https://blogs.nvidia.com.tw/2014/09/accelerate-machine-learning-cudnn-deep-neural-network-library/ (visited on 03/30/2017).

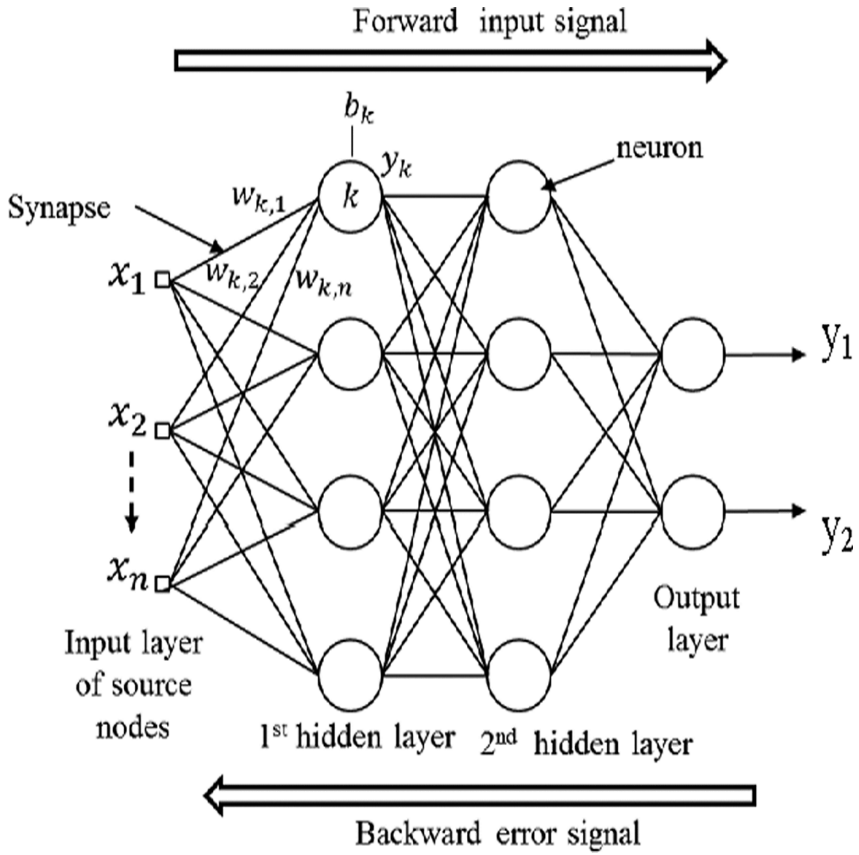
[4] M. Urban J. Matas O. Chum and T. Pajdla. "Robust wide baseline stereo from maximally stable extremal regions". In: *Proc. British Machine Vision Conference* (2002), pp. 384–396.

[5] Y. Boureau K. Gregor M. Mathieu K. Kavukcuoglu P. Sermanet and Y. LeCun. "ImageNet classification with deep convolutional neural network". In: *Proc. Conference on Neural Information Processing Systems* (2012), pp. 1097–1105.

Discussion

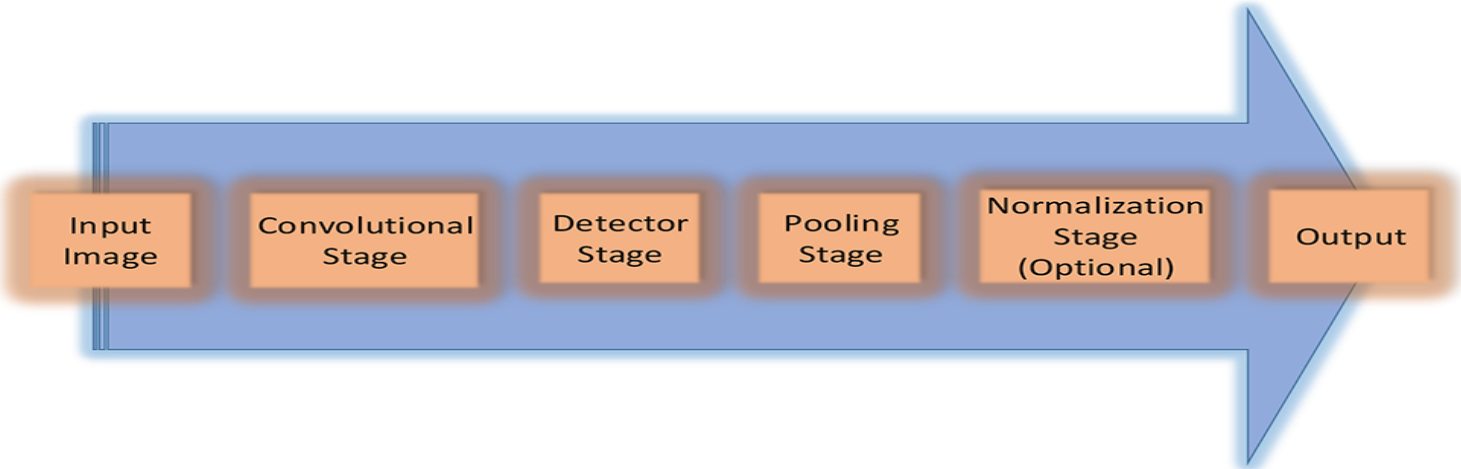
Thank you

Convolutional Neural Network



- CNN is neural networks that use convolution in place of general matrix multiplication in at least one of their layers.

Convolutional Neural Network



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Convolutional Neural Network

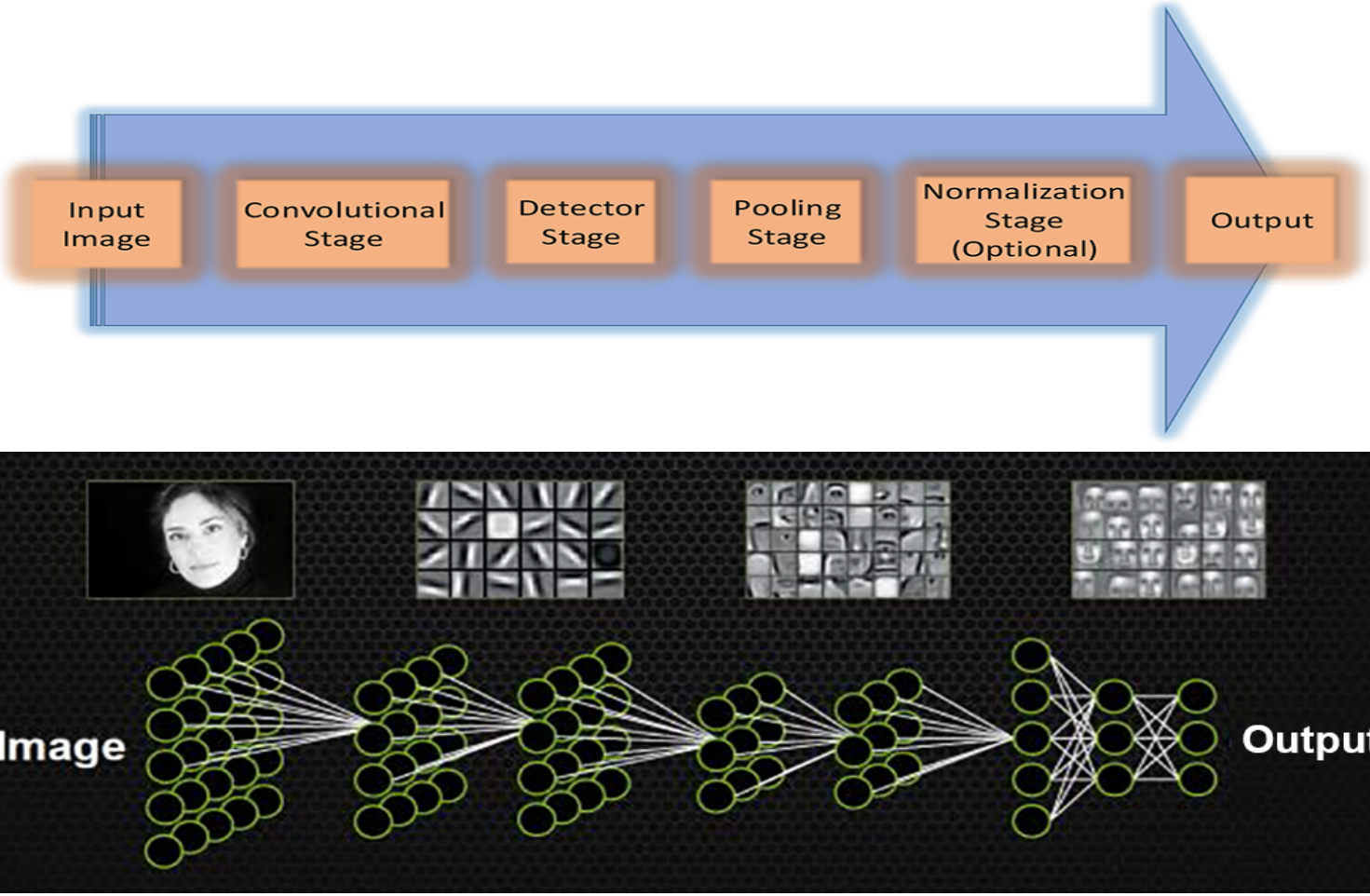

Figure 20: CNN work-flow[2]

back

[2] Larry Brown. *Using cuDNN depth neural network*. 2014. URL: https://blogs.nvidia.com.tw/2014/09/accelerate-machine-learning-cudnn-deep-neural-network-library/ (visited on 03/30/2017).