Tutorial

ACCV 2018

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Facial Micro-Expression Analysis – A Computer Vision Challenge

III. ME Spotting

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Outline

ME spotting pipeline

Pre-processing steps

- Facial Landmark Detection & Tracking
- Face Registration
- Optional steps (Masking, Region division)

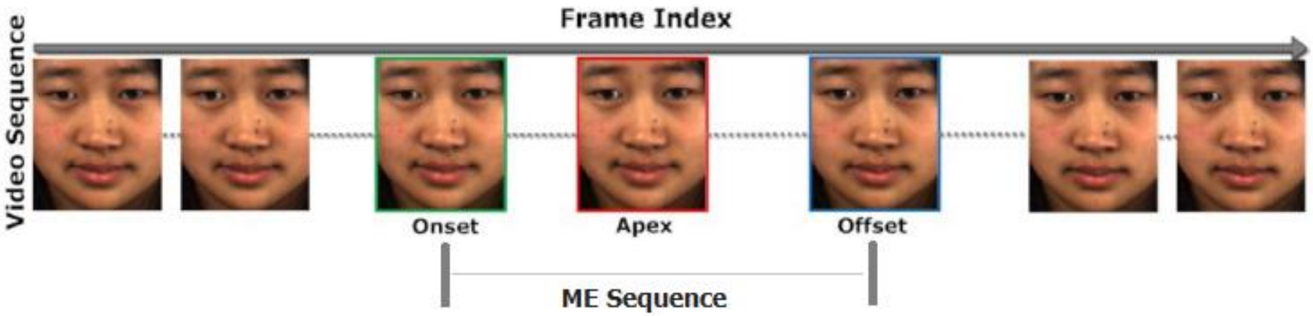
Approaches

- Early attempts with posed data
- ME sequence spotting – Feature difference (FD) analysis
- ME apex spotting
- **Highlighted Work:** Automatic Apex Frame Spotting in Micro-Expression Database

ME spotting

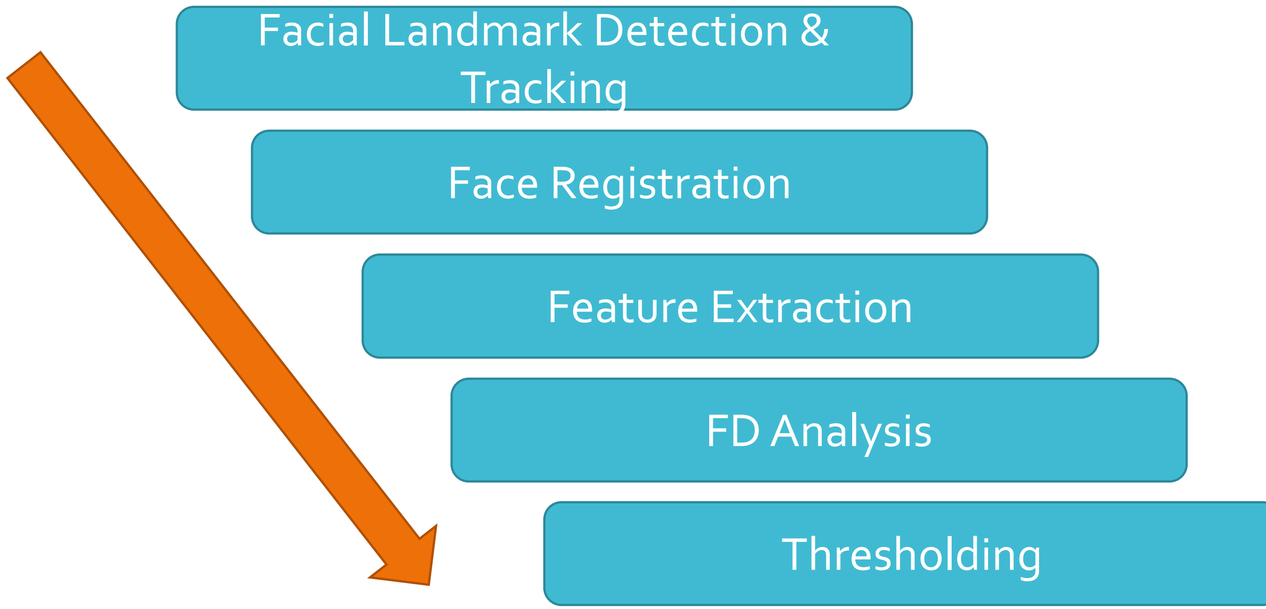
- **Spotting**
  - Automatic detection of the temporal interval of a micro facial movement in a sequence of video frames

- **Two Current Flavours:**
  - Spotting ME sequence or window of occurrence
  - Spotting ME apex frame



ME Spotting Pipeline

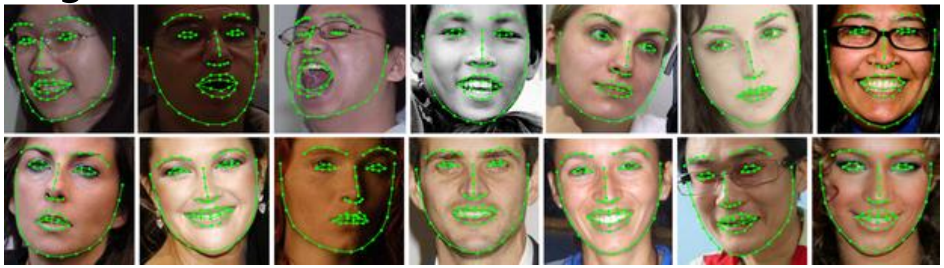
Typically[†], a ME spotting process will follow these steps:



[†] A majority of spotting works use this pipeline. There are a few works that treat spotting as a classification problem; hence they may have a pipeline that is more similar to one of recognition.

Facial Landmark Detection & Tracking

- **Landmark Detection**
  - Some early works manually annotate the first frame with facial landmarks, and proceed to track (Polikovsky et al., 2013)
  - To automate this process, later works apply automatic facial landmark detection:
    - Active Shape Model (ASM)
    - Discriminative Response Map Fitting (DRMF)
    - Constraint Local Model (CLM)

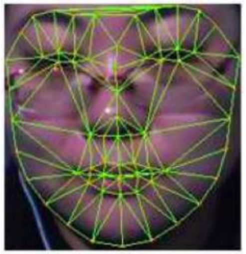


iBUG group, Imperial College London

- **Tracking**
  - Kanade-Lucas-Tomasi (KLT) algorithm
  - Auxiliary Particle Filtering (APF) algorithm

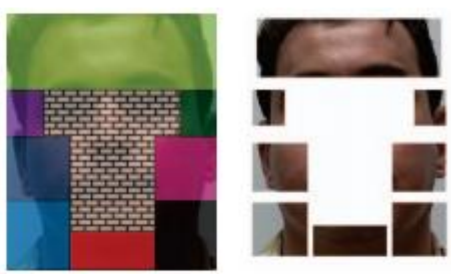
Face Registration

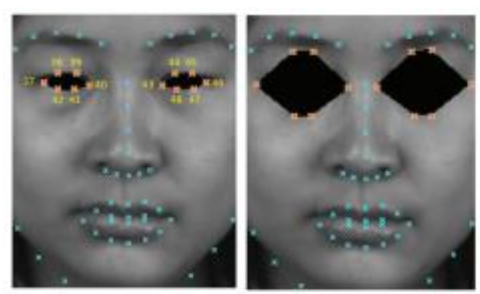
- **Image Registration**
  - A process of aligning two images (the reference and sensed images) in a geometrical manner.
  - In ME ➔ Useful to remove large head translations and rotations that might affect spotting or recognition task.
- 2 major categories of approaches used by ME works:
  - **Area-based (a.k.a. template matching or correlation-like)** – windows of predefined size / entire image utilized to estimate correspondence between images. ➔ **2D-DFT** used by Davison et al. (2016)
  - **Feature-based** – features from local structures (points, lines, regions) are used to find pairwise correspondence between images
    - **Simple affine transform** used by Shreve et al. (2011), Moilanen et al. (2014)
    - **Local Weighted Mean (LWM)** used by Li et al. (2017), Xu et al. (2017) seeks to find 2D transformation matrix using 68 landmark points of the face

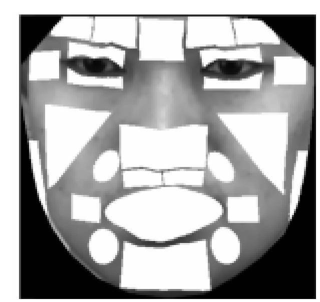


(Optional) Masking

- A **masking** step can be useful to remove noise caused by undesired facial motions
  - **Shreve et al. (2011)** – used a “T-shaped” static mask to remove middle portions of the face and the eyes
  - **Liong et al. (2016)** – used eye regions extracted based on facial landmarks to reduce false spotting of eye blinking motion
  - **Davison et al. (2016)** – used a binary mask to obtain 26 FACS-based facial regions, which were representative of locations of the face containing a single or a group of AUs







(Optional) Region Division

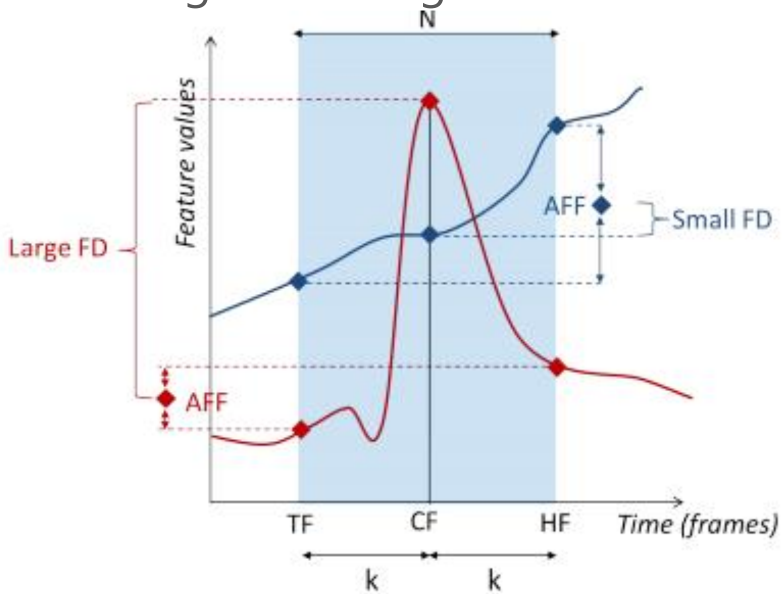
- Psychological findings (Porter & ten Brinke, 2008): ME analysis should be done on the upper and lower halves separately instead of together
- **Region division** encourages splitting the face into important separate segments to achieve "localized spotting"
  - **Ad-hoc ROI segments:**
    - 3 regions (upper, middle, lower); **(Shreve et al., 2009)**
    - 8 regions (forehead, left & right of eye, left & right of cheek, left & right of mouth, chin) **(Shreve et al., 2011)**
    - 4 quadrants **(Shreve et al., 2014)**
    - FACS action unit (AU) regions **(popular in many works)**
  - **Block/grid segments:**
    - $m \times n$ blocks **(popular in many works)**
  - **Delaunay triangulated segments (Davison et al., 2016)**

Early Attempts on posed data

- **Polikovsky et al. (2013)**
  - 3D gradient histograms as descriptor to distinguish onset, offset, apex, neutral
  - Drawbacks:
    - Used posed data which is not challenging and unnatural
    - Treat spotting as a classification problem!
- **Shreve et al. (2013)**
  - Optical strain method to spot macro- and micro-expressions
  - Reported good results (77/96 spotted) on their small, unpublished posed dataset

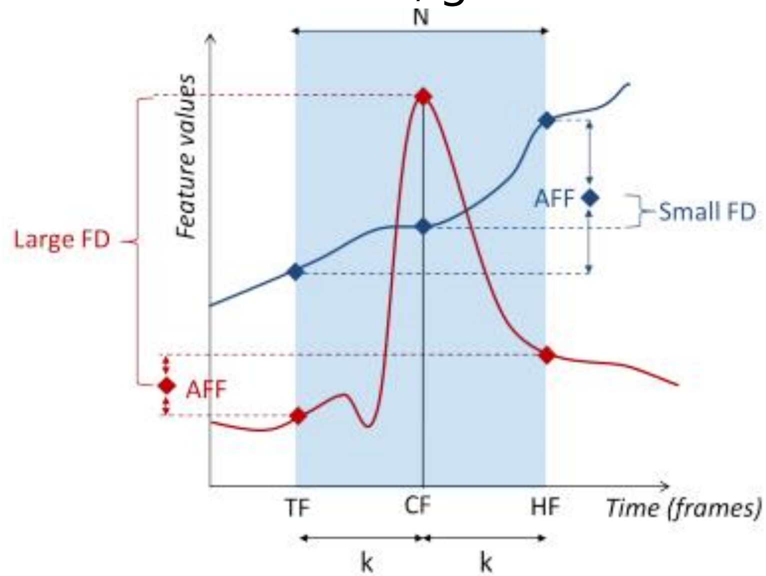
Feature Difference (FD) Analysis

- **FD Analysis:** Compares differences of video frame features within a specified interval
- **Terminologies:**
  - CF: Current frame, N : Micro-interval
  - HF: Head frame (k-th frame after CF)
  - TF: Tail frame (k-th frame before CF)
  - $k = \frac{1}{2}(N - 1)$
  - AFF: Average feature frame, feature vector Representing the average of features TF and HF.

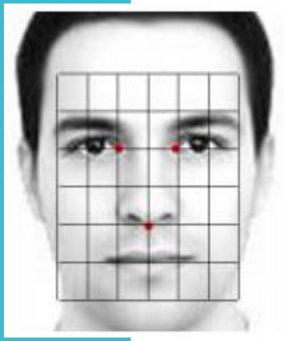


Feature Difference (FD) Analysis

- **FD Analysis:**
  - Compare the features of CF against its AFF by computing the FD of the pair of feature histograms using χ^2 distance
  - Do this for all CFs, except for the first and last k frames
- **Intuition**:
  - Large FD ➔ A rapid facial movement, onset-offset occurs within the time window
  - Small FD ➔ A slower, gradual facial movement



Feature Difference (FD) Analysis



- **Localizing spotting:**
  - For each CF, FD values are computed for each block (e.g. 6x6 grid = 36 blocks)
  - Since the occurrence of an ME will result in larger FD values in some (but not all) blocks, we take the average of M largest FDs as the difference vector

$$F_i = \frac{1}{M}\sum_{\beta=1}^{M} d_{i,j_\beta}$$

  - The contrasted difference vector finds how far it is from the average F_i of TF and HF

$$C_i = F_i - \frac{1}{2}(F_{i+k} + F_{i-k})$$

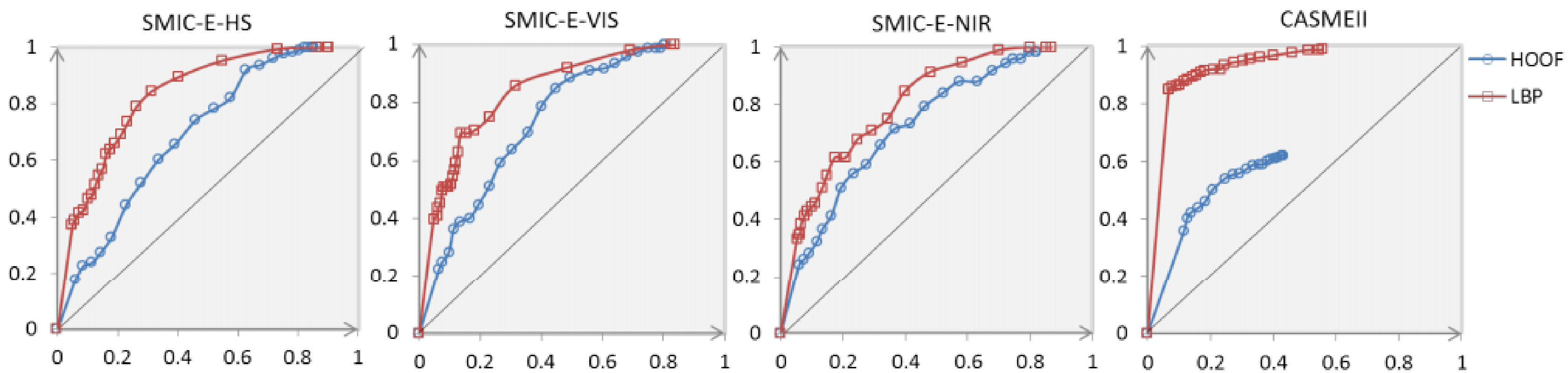
- **Determine threshold**:
  - Threshold ➔ $T = C_{\text{mean}} + \tau \times (C_{\text{max}} - C_{\text{mean}})$
  - $\tau = [0, 1]$ is a parameter for obtaining different thresholds

Feature Difference (FD) Analysis

- **Peak detection:**
  - Minimum peak distance for peak detection is set to $k/2$
  - Spotted peaks are compared with ground truth labels
    - If one spotted peak is located within the frame range of $\left[onset - \frac{N-1}{4}, offset + \frac{N-1}{4}\right]$, the frames in the spotted sequence are counted as true positives, otherwise the N frames will be counted as false positive frames.

Some results from Li's work

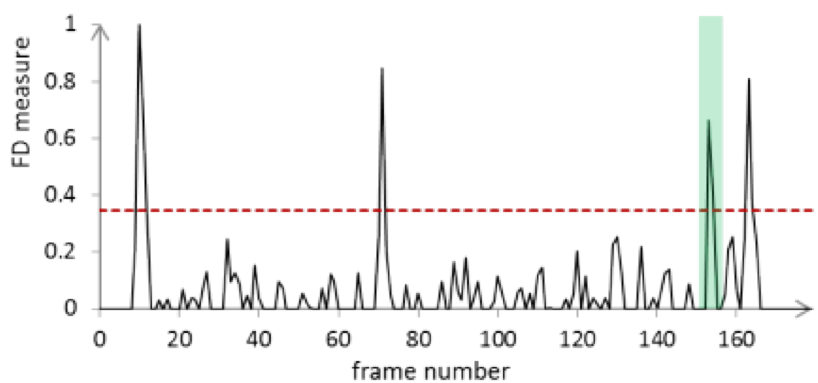
- **Spotting on CASME II and the SMIC datasets**



AUC values of the ME spotting experiments

	SMIC-E-HS	SMIC-E-VIS	SMIC-E-NIR	CASMEII
LBP	83.32%	84.53%	80.60%	92.98%
HOOF	69.41%	74.90%	73.23%	64.99%

- **Challenging scenarios**:
  - E.g. At the given threshold, one true ME spot, three false eye blink spots



Attempt: Exclude eye regions, eye-blink detector to exclude blinks…
FPR ↓ TPR ↓

Features for FD Analysis

- A majority of works that applied FD Analysis opted for different feature choices:

Feature	First Work to Use
LBP	Moilanen et al. (2014)
HOG	Davison et al. (2015)
MDMD	Wang et al. (2016)
3D HOG, Optical Flow (OF)	Davison et al. (2016)
HOOF	Li et al. (2017)
Riesz Pyramid	Duque et al. (2018)

- Other methods:
  - Optical flow vectors of small local regions, integrated into spatio-temporal regions to find onset/offset times **(Patel et al., 2015)**
  - Random walk model to compute probability of containing MEs **(Xia et al., 2016)**

Performance Metrics & Specific Settings

- ME spotting is akin to a binary detection task (present / not present)
- Typical detection performance metrics:
  - TPR
  - FPR
  - ROC

$$\text{TPR} = \frac{\text{Number of frames of correctly spotted MEs}}{\text{Total number of ground truth ME frames from all samples}}$$

$$\text{FPR} = \frac{\text{Number of incorrectly spotted frames}}{\text{Total number of non-ME frames from all samples}}$$

- The micro-interval $N = 0.5s$ is taken as the presumed maximum possible duration of MEs
  - Li et al. (2017)'s work used $N = 0.32s$ which corresponds to $N = 65$ for CASME II

Automatic Apex Frame Spotting in Micro-Expression Database

ACPR 2015

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Yee-Hui Oh, Raphael C.W. Phan

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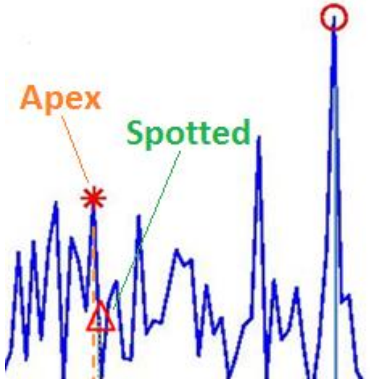
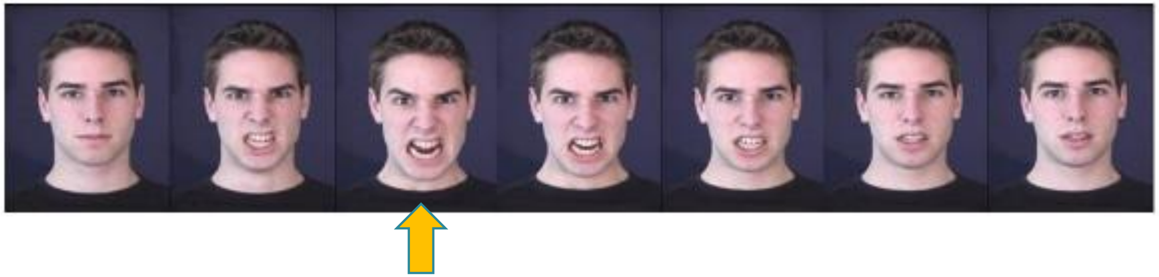
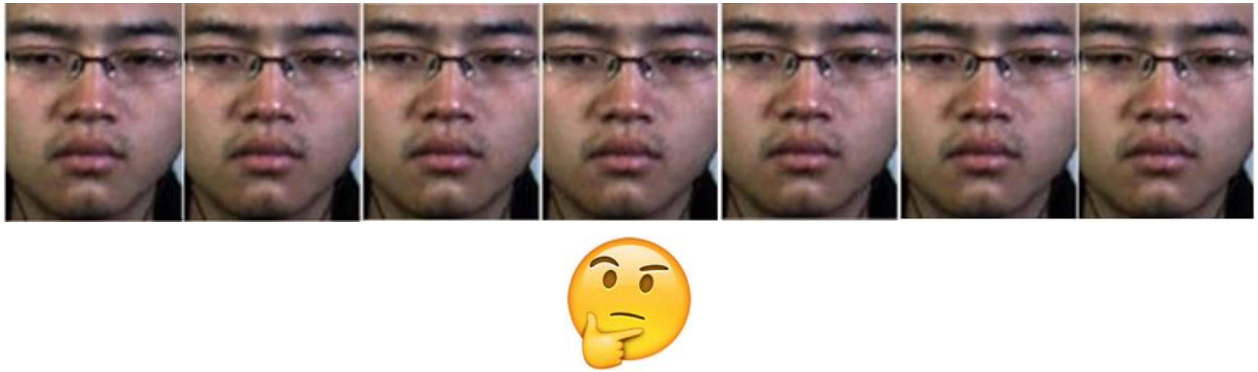


Spotting the apex frame

- **Can you tell which frame is the apex (with the strongest indication of emotion) ?**



- **How about this ?**

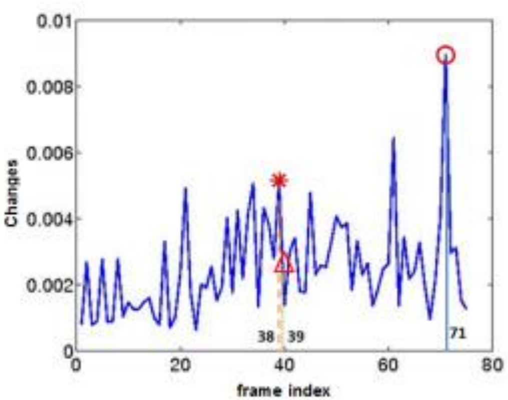


Spotting the apex frame

- **Apex frame spotting:**
  - Apex frame: the instant that is the most expression emotional state in the sequence
  - Motivation: The apex frame is a potentially useful piece of information that may be helpful to recognition (spotting sequences tend to have a high margin of error)
- The first work to attempt this: Yan & Chen (2017)
  - CLM, LBP and OF were used to obtain features
  - Frame with largest feature magnitude is selected as the apex
  - **However, is the frame with the strongest magnitude a good candidate?** Can the presence of noise (eye blinks, large movements) affect this criterion?

Exhaustive binary search strategy

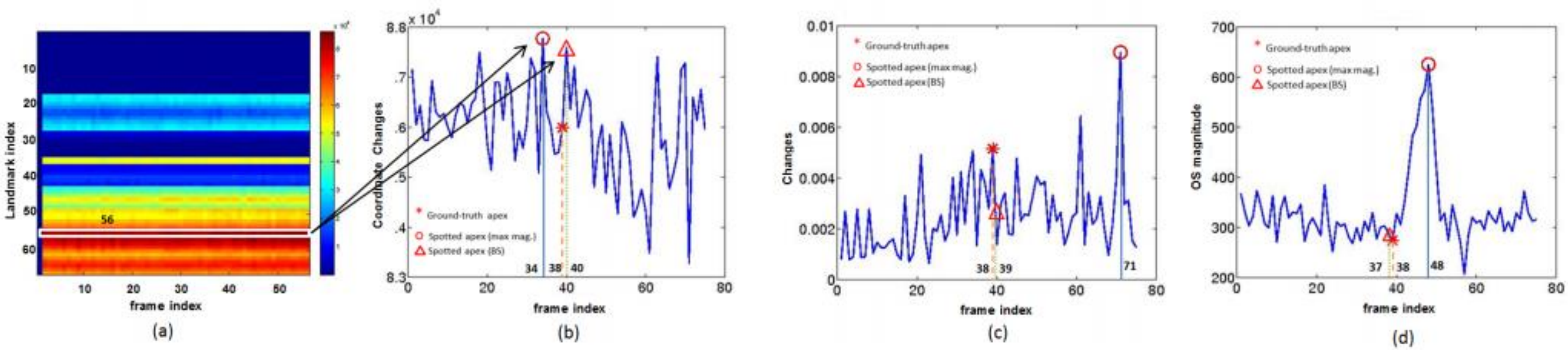
- This is as simple as it gets….
- Exhaustive binary search strategy recursively searches through the set of candidate peaks by further splitting the partition that possesses the larger sum of feature magnitudes. Search stops when the final partition contains only 1 candidate peak, hence can no longer be split.



Algorithm 1 Binary Search

$l \leftarrow$ split level
$S \leftarrow$ set of candidate peaks, p_i
Initialize $l = 0$, $S_c \epsilon \forall p_i$
repeat
  Split half S_c to S_0, S_1
  $S_c \leftarrow max(|S_0, S_1|)$
  $l \leftarrow l + 1$
until $S_i = 1$

Searching for the apex frame



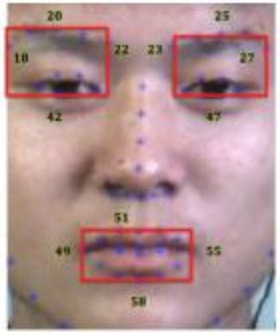
- The density heatmap shows the landmark # that contains the most changes in the video
- The proposed binary search strategy is able to get as close as possible to the g/t apex instead of doing the “greedy”, i.e. going for the max magnitude

Results

- **Performance metrics:**

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|e_i|$$

$$SE = \frac{\sigma}{\sqrt{n}},$$



- **Results:**

	Baseline [17]		BS-whole face		BS-RoIs	
Methods	MAE	SE	MAE	SE	MAE	SE
CLM	21.94	1.00	**17.21**	0.89	**17.21**	0.89
LBP	17.75	0.90	**15.54**	0.80	**13.55**	0.79
OS	18.98	0.95	**16.57**	0.87	**14.43**	0.83

	Whole face		RoIs	
Methods	F-value	p-value	F-value	p-value
CLM	20.69	0	20.69	0
LBP	8.31	0.0043	6.25	0.0131
OS	6.50	0.0114	7.90	0.0053

Spotting – how important is it?

- **Spotting** - Given a long untrimmed video, these are essential targets, our "wish list":
  1. Able to differentiate macro-expressions and micro-expressions

     ➔ CAS(ME)^2 needs mileage!
  2. Able to extract "sufficiently good" ME sub-sequences that can be passed on to recognition task

     ➔ Apex spotting does it from a different perspective…

2nd MEGC in FG 2019 has a new spotting challenge!

End of Part 3

Questions?