

## **Multimedia Signal Processing**

An Overview for Content-Based Information Retrieval

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- Motivation & focus
  - The need for audio, image & video processing for semantics extraction
- Digital representation of audio, image and video Data
  - Uncompressed & compressed
- Feature extraction
  - What's important?
  - Colour, texture, shape, motion, volume, pitch, ..
  - Using features
- Multi-modal content analysis
  - Bringing it altogether ... and adding text analysis
- Conclusion









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#### What's Not Covered?

#### Text analysis

- Although show how text can be used with the techniques presented

#### Deep discussion of audio processing

- Only scratch the surface
- Examples shown are very rudimentary
- Much more sophisticated work by <u>real</u> experts
- [Sikora, 06], [Sandler, IEEE Trans ASLP-07], [Richards, IEEE Trans CSVT-07]





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## Hypothesis

# PhD students never had it so good!

Grumpy Supervisor Theorem "It wasn't like that in my day!"



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#### Lecture Motivation & Focus



#### **Growth of Multimedia**



- Unprecedented growth in the amount and nature of multimedia content available
- Decreasing cost of digital capture and storage
  - 490 digital photographs taken with each digital camera in the EU in 2006
  - Half a trillion digital images will be captured in 2009
  - Camera production reaching 89 million units in 2010 (not including camera phones!)
  - Worldwide camera phone sales: 370 million units in 2005,
    29 billion digital images: 847 million units in 2009
  - CCTV: 4.2 million cameras in U.K. (1 for every 14 people!)









#### PhDs Never Had it So Good

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## Lots of data means lots of interesting problems!







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- Useless unless we can access relevant content
- Index the audio/image/video data based on its contents
- Content-based Information Retrieval (CBIR)
  - Indexing performed automatically (ideally!)
  - Based on depicted 'real world' content
    - Who, what, where, why, when, how, ...
- Advanced interaction, improved compression, 'intelligent' content, ...
- Manual indexing of multimedia content for retrieval is time consuming & expensive
- 8 hours for 1 hour of video!



#### Signals & Semantics



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- Clear need for machine computable techniques for extracting real world knowledge ... semantics
- From signals to semantics:
  - Image/Audio/Video Processing
    - image in -> image out
  - Image/Audio/Video Analysis
    - image in -> measurements out
  - Image/Audio/Video Understanding
    - image in -> high-level description out
      - [Young et al, Image Processing Fundamentals, CRC Press LLC, 1997]









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#### Problem:

- Difference between what we can measure from a visual signal and what this means

#### The "Semantic Gap"

- "...the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation."
  - [Smeulders et al, Content-based image retrieval at the end of the early years. IEEE transactions PAMI, 22 12:1349 1380, 2000.]





#### The Semantic Gap



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- Consider image data ...
- "Un bon croquis vaut mieux qu'un long discours"
- "A good sketch is better than a long speech"
  - Napoleon Bonaparte (1769 1861)
- "A picture shows me at a glance what it takes dozens of pages of a book to expound."
  - Ivan Turgenev (in Fathers and Sons, 1862)
- "A picture is worth a 1,000 words"
  - Fred R. Barnard, 1921, trade journal Printers' Ink, promoting the use of images in adverts on streetcars (not Confucius!)





#### The Semantic Gap



- "The purpose of computing is insight, not numbers."
  - Richard Hamming (1915-1998)











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#### Approaches

• A hugely active research field:

- Many National and EU projects
  - K-Space, aceMedia, BOEMIE, MESH, ...
- Many different applications and content domains
  - News, sports, movies, personal collections, ...
- Many different approaches
  - Too many to list!
- ↓ €€€M of funding, 00's of PhDs, 000's of papers, ...
- The Semantic Gap is a Semantic Chasm!







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#### PhDs Never Had it So Good

- Lots of data means lots of interesting problems!
- Semantic gap means lots of exciting interdisciplinary papers and theses!











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#### Bottom-up

- Focus on specific application niches & challenges ... but changing to more generic application scenarios
  - Mature solutions for many complex analysis tasks now available
- Top-down (Semantic Web)
  - Tools for ontology creation and management, linking lowlevel features to concepts
    - Availability of custom-built ontologies defining important concepts
- → Generic
  - Robust machine learning approaches broadly applied to detect many different concepts
    - Classifier banks, variety of early and late fusion strategies
       with promising results



#### Examples



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- Invariant image features
  - [Lowe, IJCV-04]
  - [Van Gool, ECCV-06]
- Recognising people
  - [Viola, CVPR-01]
  - [Zisserman, BMVC-06]
- Recognising settings and objects
  - [Szeliski, SIGGRAPH06]
  - [Triggs, CVPR-05]

- Recognising actions
   [Laptev, ICCV07]
- AV Events
   [Chang CVPR-07, ICME-06]
- Audio semantics
  - [Sikora, 06]
  - [Sandler, IEEE Trans ASLP-07]
  - [Richards, IEEE Trans CSVT-07]





#### Examples



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#### Top-down

- Knowledge assisted analysis using ontologies
  - [Avrithis, IEEE Trans CSVT 07]
  - [Staab, SAMT 06]
- LSCOM: Large Scale Multimedia Ontology for Multimedia
  - [Hauptmann, ICME-06]
- → Generic
  - MediaMill 100+ concept detection
    - [Worring, IEEE Trans MM 07]







#### Signals & Semantics

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- Usually the first step is in calculating some measurements from the signal
- Termed *features* 
  - Can be used to train classifiers, mapped to higher level concepts via ontologies and used in inference processes
- This lecture focuses on "low-level" feature extraction
- What can (should) we measure from the signal?



#### **Lecture Overview**



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- Focus on feature extraction for CBIR
- By necessity, need to understand how images, video and audio are represented
- Given this, we describe a selection of useful features
- Show examples of the usefulness of individual features
- Show examples of how combinations of features can be used
- Cover a lot, but pointers to further reading





#### **The Basics**

# AV Capture, Representation and Compression



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#### **Digital AV Capture**



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- An image is captured when a camera scans a scene
  - Colour => Red (R), Green (G) and Blue (B) array of samples
  - Density of samples (pixels) gives resolution
- A video is captured when a camera scans a scene at multiple time instants
  - Each sample is called a frame giving rise to a frame rate (frames/sec) measured in Hz
    - TV (full motion video) is 25Hz
    - Mobile video telephony is 8-15 Hz ... jerky
- Audio is captured when a microphone temporally samples sound waves















#### Video Data

#### Desktop PC

- CIF (352 x 288), 8 bpp, 30hz = 8.7 MB/sec
- 30 sec clip = 261 MB
- Video to mobile device
  - QCIF (176 x 144), 8 bpp, 30 hz = 2.2 MB/sec
  - 30 sec clip = 65 MB
- High Definition TV (HDTV)
  - 1280 x 720, 24 bpp, 50 hz
    = 0.4 GB/sec
  - 2.5 hour movie = 3.4 TB







Compression

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- When captured, audio/video data is referred to as as "raw" or "uncompressed"
- Undergo software/hardware process to compact data:
  - Termed "compression" or "encoding"
  - Results in a bitstream that can be stored or transmitted
  - Requires a (less) complex process to uncompress/decode before it can be displayed/heard
- Implications for CBIR
  - Features used for retrieval can be extracted from:
    - Encoded data ... termed compressed domain
      - fast (real-time), simply parsing the bitstream
    - Raw data ... termed uncompressed domain
      - slower (requires decode) but less restrictive
      - i.e. greater range of more expressive features possible DUBLIN CITY UNIV





#### Compression

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#### Two types:

- Lossless: doesn't change data "simply" reorganizes
  - Used in medical applications (e.g. X-Rays) and document scanning (e.g. FAX)
- Lossy: throws some data away during encoding
  - Used in most multimedia applications
- Popular AV compression standards
  - JPEG (still images)
  - JPEG 2000 (enhanced functionality/quality)
  - MPEG-1 (video from CD-ROM)
  - MPEG-2 (digital TV, DVD)
  - MPEG-4 (mobile and content-based functionality)
  - H.264 (advanced video coding)
  - Note: MP3 = MPEG-1 layer 3 audio encoding





#### Image Compression

#### 

## Use frequency domain analysis The discrete cosine transform (DCT)

Spatial Domain
 Highly Textured
 Fine Detail

- Low Pass Filter
- Ignore high frequency infoEven better compression



 DCT Domain
 Energy Compaction
 Less information to store or transmit over network

- Reconstruction
- Use Inverse Transform
- Low perceptual losses





#### **Image Compression**



#### Original image



Output image

MT = LEVEL		
ispinets/	ome/W/rikroege	PANES
SSD THET?	Nome /u/rikroege	NA
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Difference image		
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#### **Video Compression**



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## **Audio Compression**



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- Human sensitivity to sound is non-linear across audible range (20Hz - 20kHz)
  - Audible range broken into regions where humans cannot perceive a difference called the critical bands
- Polyphase Filter Bank:
  - Transforms samples to frequency domain in 32 subbands
- Psychoacoustic Model:
  - Calculates acoustically irrelevant parts of signal
- Bit Allocator:
  - Allocate bits to subbands according to input from psychoacoustic calculation.
- Frame Creation:
  - Generates an MPEG-I compliant bit stream





FilterBank: does a time-to-frequency mapping

Psychoacoustic Model: calculates a just-noticable noise level Bit/Noise Allocation: tradeoff bitrate & masking requirements Bitstream Formatter: efficient encoding and formatting of stream

D. Pan, "A Tutorial on MPEG/Audio Compression", IEEE Multimedia Journal, 1995.

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- Group 12 samples from each subband and encode them in each frame (=384 samples)
- Each group encoded with 0-15 bits/sample
- Each group has 6-bit scale factor
  - max. value of samples within group of 12 samples.










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# Audio, Image and Video Features





#### What's Important?

# Consider still images

- Colour
- Texture



Highly textured • The feel, appearance, <u>consistency</u> of a surface

No texture

- Distribution over the entire image?
- Of specific parts of the image or of the objects present?
  - Could just overlay grid
  - Shape of objects/regions is important













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#### What's Important?

#### Consider video

- Extends images along temporal dimension
- Can measure colour & texture for each individual frame
- Can now also measure "motion":
  - Where a pixel moves from one frame to the next
  - What's changed from one frame to the next
  - Already do this for compression!
- Two kinds of motion we might want to measure:
  - Global over the entire frame, corresponds to camera motion (pan, zoom, tilt, etc)
  - Local motion object moving over background



# Colour



- Colour is visually important to humans
- Colour features and similarity metrics easy to compute
  - Histogram [Swain and Ballard, 1992]
    - Most commonly used structure to represent global image features.
    - Invariant to translation and rotation and can be made invariant to scale by normalisation
    - MPEG7 Scalable Colour Description:
      - H(16 levels) S(4 levels) V(4 Levels) histogram encoded with a Haar transform for efficiency & scaling









# Colour



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- Other MPEG-7 Colour Descriptors [Manjunath et al 2002]
  - Colour space and quantization
    - Used in conjunction with other descriptors
    - RGB, YCbCr, HSV, HMMD, monochrome (Y)
  - Dominant colour
    - Targeted at similarity retrieval in image databases
    - Algorithm involves a sequence of clustering steps
    - Descriptor = colour vector, % pixel area, variance, spatial coherency of the dominant colours
  - Colour structure
    - Colour distribution + local spatial structure of colour
  - Colour layout
    - DCT applied to 2D array of local representative colours in Y or Cb or Cr planes - compact & resolution-invariant





#### Texture



Simple texture descriptors [Pratt, 1991]:

- Autocorrelation function
- Co-occurrence matrices
- Edge frequency
- Primitive length
- More sophisticated (based on transforms and/or filtering)
  - Wavelet [Mallat, 1990], Haar [Theodoridis, 1999], Gabor [Bovis, 1990]
- Others:
  - Mathematical morphology
  - Fractals









#### Example: MPEG-7 Edge Histogram

- Represents the global (and possibly local [Won, 2002]) spatial distribution of edges
  - Need to first generate edge map
    - Roberts, Sobel and Prewitt, Canny, ...
  - Build histogram based on 5 edge types











#### Texture



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#### • Example: Haar transform

- Image decomposed into frequency bands





- H1, H2 and H3 provide different spectral characteristics.
  - H2 area can be seen as a low-pass horizontal filtering followed by high-pass vertical filtering thereby emphasizing vertical vollege DUBLN (TY UNIVERSITY frequencies.





#### Image Segmentation

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- Breaking up an image into smaller more meaningful segments
  - Ideally segments should be real world "objects"
  - But this is ill-posed ... even for us!
- What constitutes an object?
  - Depends on application, requires user interaction or *a priori* knowledge



Face or musician?



Eskimo or Native American?



Two faces or Vase?



Faces, heads, full bodies?

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#### **Segmentation Applications**

#### Multimedia information retrieval

- Can use regions to extract rich semantic information
- Shape analysis
  - OCR, multimedia IR, shape classification, ...
  - Segmentation is often a necessary pre-processor
- Medical image analysis
  - X-Rays, CAT scans, MRI ...
  - Automatic diagnosis, classification, ...
- Industrial Vision Systems
- Knowledge Assisted Analysis (KAA)
  - What objects are in the image?!







- Usually, group pixels into regions on the basis of a homogeneity criterion:
  - Colour and texture are frequently used
  - Hopefully, output segments reflect real-world structure of scene
  - Very active research area for many years:
    - Graph theoretic models
    - Markov Random Fields
    - Statistical/Probabilistic solutions
    - Semi-automatic approaches, ...









#### Segmentation Challenges

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#### Problems:

- Over segmentation:
  - Segmentation algorithm based on merging stopped too early
- Under segmentation:
  - Segmentation algorithm based on merging stopped too late
- Key is finding smarter merging process and/or "clever" stopping criteria









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#### Segmentation Challenges (II)

- Segmentation is an ill-posed problem.
- What criteria should be optimized?
  - Which features are most important?
    - Color? Texture? Edges? ...
  - What grouping principles are most important?
    - Similarity? Proximity? Symmetry? ...
  - In what proportion, how do they interact?
    - 0.5 \* similarity + 0.2 \* proximity + 0.3 \* symmetry = good segmentation?
  - How to efficiently optimize such criteria?





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#### Segmentation Challenges (III)

- Before better segmentation algorithms can be developed we need to answer:
  - What makes a particular segmentation "good", what makes it "bad"?
  - What makes one segmentation "better" than another one for a given application?
- Segmentation evaluation:
  - May be possible to develop a better understanding of this through development of formal methods for evaluating segmentation
- Key research topic:
  - A comprehensive framework for characterising segmentation algorithms and evaluating their performance in the context of specific applications.







#### Syntactic Segmentation



















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This work is supported by Science Foundation Ireland under grant 07/CE/I1147

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#### Demo 1: Region-based Segmentation

http://kspace.cdvp.dcu.ie/platform/platform.html

[McGuinness et al, Image Segmentation Evaluation Using an Integrated Framework, VIE 2007]



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# **Objects vs. Regions**

- Real-world objects tend to be made up of a number of distinct regions
- With state of the art it is reasonably straight forward to segment into regions
- How do we group regions into objects?
- Need:
  - A apriori domain specific knowledge
    - [Dasiopoulou et al, Knowledge-Assisted Semantic Video Object Detection, IEEE Trans CSVT,Oct 2005.]
  - User interaction









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## Demo 2: Interactive Image Segmentation

http://kspace.cdvp.dcu.ie/public/interactive-segmentation

#### [McGuinness & O'Connor, A Comparative Evaluation of Interactive Segmentation Algorithms, submitted to Pattern Recognition]





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# Seeded Region Growing

- Simple and computationally inexpensive
- Input set of seed points grouped into n disjoint sets S where n is the number of desired regions
- For our case, n = 2, giving two sets of seed pixels: S1 for the object seeds and S2 for the background seeds.
- At each step, a single pixel adjacent to the object or background seeds is added to one seed set.
- The pixel is chosen to be the one with minimum distance to the average color of the pixels in S1 or S2
  - [Adams and Bischof, PAMI 2008]



#### **Interactive Graph Cuts**



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- Formulates the interactive segmentation problem within a MAP-MRF framework
- Minimise a cost function that captures both the hard constraints provided by user, and the soft constraints expressing the relationships between pixels
- Image and user interactions are combined into a weighted undirected graph
  - [Boykov and Jolly ICCV 2001]



# Simple Interactive Object Extraction



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- Uses the pixels marked by the user to build a color model of the object and background regions.
- Classifies the pixels in the image as either object or background based on their distance from this model.
- Recently been integrated into the popular imaging program GIMP as the Foreground Select Tool.
- Color signatures are represented as a weighted set of cluster centres
- Unknown image pixels are then classified as foreground or background according to the minimum distance to any mode in the foreground or background color signatures.
  - [G. Friedland et al, 2005]





 Construct a hierarchical Binary Partition Tree (BTP) using the Recursive Shortest Spanning Tree (RSST)

**M-RSST** 

- Modify segmentation using syntactic features
- Leaf nodes assigned labels according to the pixels marked by the user as object and background.
- Labels the propagate upward toward the root of the tree, resolving conflicts on the way.
  - [Adamek T., PhD, 2006[







# Shape



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#### Geometric [Jain,19988]

- Area: the number of pixels present in a region

$$Area = \int_{a}^{b} f(x) dx$$

- Perimeter: the number of pixels on boundary



- Aspect: ratio between major and minor axes





#### Shape



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#### Statistical [Jain, 1988]

- Moments:

$$m_{ij} = \frac{\sum_{x=1}^{N} \sum_{y=1}^{N} x_i y_j f(x, y)}{\sum_{x=1}^{N} \sum_{y=1}^{N} f(x, y)}$$

- m10 is the x component of the mean
- m01 is the y component of the mean
- Central moments:

$$\mu_{ij} = \frac{\sum_{x=1}^{N} \sum_{y=1}^{N} (x - \mu_x)^i (y - \mu_y)^j f(x, y)}{\sum_{x=1}^{N} \sum_{y=1}^{N} f(x, y)}$$

- Compute the orientation of a shape as:

$$heta = rac{1}{2} arctan rac{2 \mu_{11}}{\mu_{20} - \mu_{02}}$$







#### Curvature Scale Space [Mokhtarian, 2003]

- A multi-scale representation of the curvature points of the shape
- Curvature points are inflection points in the shape
- If we consider the contour as a signal, it's scale space is obtained by convolution with a Gaussian of increasing width (standard deviation)
- Adopted by MPEG-7 standard







# Shape



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- Curvature Scale Space (CSS)
  - Zero-crossing point maxima of the CSS contours used as a shape descriptor;
  - Very compact, fast matching;
  - Robust with respect to noise, scale and orientation changes;
- Two major drawbacks:
  - Ambiguity with regard to concave segments,
  - Inability to represent convex segments.
- Development of Multiscale Convexity-Concavity (MCC) measure [Adamek, 2004]









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- ✤ MCC representation
- Size normalized contour:

 $C(u) = ((x(u), y(u)), \ u \in \langle 0, N \rangle$ 

 Convolution with Gaussian kernels:

$$\phi_{\sigma}, \sigma \in \{1, 2, \dots, \sigma_{\max}\}$$

 Convexity/concavity measured as contour displacement between two consecutive scale levels









#### Demo 3: Shape Matching

[Adaemek & O'Connor, A Multi-scale Representation Method for Non-rigid Shapes with a Single Closed Contour, IEEE Trans. CSVT 2004]





#### **Object Matching**





#### **Detection results:**

Character	Bart	Homer	Marge	Lisa	Maggie	AVG.	
Precision[%]	98	98	92	93	90	94.2	FY COLLEGE DUBLIN
Recall[%]	49	35	29	57	31	40.2LIN CITY U	





#### PhDs Never Had it So Good

- Iots of data means lots of interesting problems!
- Semantic gap means lots of exciting interdisciplinary papers and theses!
- PhDs get to watch The Simpsons as part of their research!






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#### Word Matching in Manuscripts

- V. Lavrenko, T. Rath, and R. Manmatha, "Holistic word recognition for handwritten historical documents", DIAL 2004.
- 20 pages from the George Washington collection at the Library of Congress

Winchester: October 28. The officers w from Fort bumberland. Washington, are immedia ting; and they are allowed



# **GLARITY**



#### Word Matching in Manuscripts

- Collection segmented into words and annotated;
- Extraction of a single closed contour is crucial;
- Challenges: poor quality, contrast variations and disconnected letters;

Barrel Barrel Barrel Barrel Winchester, Minchester, Winchester, Minchester Instructions. Instructions. Instruct



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#### Word Matching in Manuscripts

- 4,856 word occurrences of 1,187 unique words
- Each of the word occurrences used as a query
- Ground-truth annotations for the word images were created manually
- Very low Word Error Rates (WER) obtainable based on shape alone
- Could be further improved using a statistical language model
  - [Adamek et al, Word Matching Using Single Closed Contours for Indexing Handwritten Historical Documents, IJDAR 2006]



# Motion



- Motion of objects, background and the camera provides significant insight into action happening
- Objects & background:
  - Practically no restrictions on the type of movement
- Camera [Akutsu, 1992]:
  - panning horizontal rotation
  - tilting vertical rotation
  - zooming focal length change
  - tracking horizontal traverse movement
  - booming vertical traverse movement
  - dollying horizontal lateral movement





# **Motion**



- Motion vectors in an MPEG bitstream provide motion information for blocks, regions and video frames
  - Can be easily extracted by parsing the bitstream
- Using motion vector information camera motion type can be estimated
  - E.g. use of a 6-parameter affine motion model fitted to extracted motion vectors.
- Even without performing classification, motion vectors can be used to estimate characteristic features over a number of frames



DCL

# Motion



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#### Motion smoothness

- Ratio between the number of image blocks with significant motion vectors and the number of blocks whose motion vectors has changed significantly.
- Motion histogram [Kobla, 1996]
  - Gives indication of global motion
- Average motion vector magnitude [Divakaran, 2000]
  - Threshold motion vectors and count the number of short, medium and long runs of zeros
  - Gives indication about the location, size and shape of the moving objects
- Motion activity [Sun, 2002]
  - Intensity, direction and spatial distribution of motion via summation of motion vectors in consecutive frames





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# Video Segmentation

- Can also break a video up into more meaningful segments like we did for images
- Temporal segmentation:
  - Segment along the temporal direction
  - Group frames into meaning groups
    - Shots, scenes, high-lights, story-lines, ...
- Spatial segmentation:
  - Apply image segmentation techniques to consecutive frames
- Spatio-temporal segmentation:
  - Group regions based on colour, texture & motion
  - Can correspond to moving object segmentation





# Shot Boundary Detection



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#### Shot Boundary Detection

- A continuous piece of video taken with one camera
- A shot cut is the abrupt or gradual transition between two shots
- Uncompressed domain:
  - Calculate colour histogram for each frame
  - Calculate difference between histograms using suitable metric
  - Keyframe: first, last, middle, closest to average histogram
- Compressed domain:
  - Parse features directly from bitstream:
    - E.g. use DCT coefficients for each frame to reconstruct approximation of image
    - E.g. motion vectors for each pair of frame and detect changes in global statistics





Shot Boundary Detection in MPEG-1/-2/-4

- Typical sequence of compressed frame types:
  - I B B P B B P B B P B B I
  - I frames: coded independently of other frames
  - P Frames: predicted from the previous I or P
  - B Frames: bi-directionally predicted from previous I/P and next I/P
- B frames could be but are not predicted from adjacent I/P frames - this indicates little commonality between these frames











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# Demo 4: Spatio-temporal video segmentation

[Marlow et al, Supervised Object Segmentation and Tracking for MPEG-4 VOP Generation, ICPR 2000]
[Brady et al, Object Detection and Tracking using an EMbased Motion Estimation and Segmentation Framework, ICIP 96]

[Gonzalez-Diaz et al, Incorporating Spatio-Temporal Mid-Leve Features in a Region Segmentation Algorithm for Video Sequences, ICIP 2008]



#### **Audio Features**



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- MPEG-7 audio:
  - Low level tools that apply to generic sounds
  - Either a single value or a sampled series
- High-level tools for specific applications such as:
  - Query by humming
  - Query by spoken content
  - Assisted consumer-level audio editing
  - "Find me more like this"
- AES 110th Convention Workshop, MPEG-7 Audio:What is it about?







#### **Audio Features**

#### Low-level audio descriptors

**Basic Spectral** 

- Spectral centroid/spread/flatness
  - Time series of moments of the spectrum
  - Indicates if spectrum dominated by low or high freqs, or whether broad or narrow band





- Temporal Timbral: log attack time and temporal centroid
- Spectral timboral: spectral centroid,

harmonic spectral centroid/deviation/spread/variation

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Spectral basis representations









# Multi-modal Content Analysis for Extracting Semantics

#### Leveraging Multimedia Features ... including Text







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# Targeting Specific Genres

- High-level metadata extraction is hard!
- Can we leverage knowledge about specific genres to help us?
  - Understand how the content is produced and reverse engineer this
  - Learn the rules followed by broadcasters, directors, editors, etc
- Problem
  - How can we do this without overly constraining our approach to one particular genre (e.g. sports, film) or subgenre (e.g. soccer, action movies)?
- Our solution
  - A pseudo-generic approach: look for atomic units that remain more or less constant across sub-genres







#### **Sports Content**





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### Sports Highlight Detection

#### Identify supergenres

- Racquet sports: tennis, badminton, table tennis, squash, ...
- Motor sports: Formula-1, speedway, ...
- Target sports: archery, darts, rifling, ...
- Court sports: basketball, volleyball, netball, ...
- Field sports: soccer, rugby, American football, Aussie rules, Gaelic
- Field sports
  - 2 opposing teams + referee
  - Enclosed playing area
  - Grass pitch + field lines
  - Commentator voice-over + crowd noise/reaction
  - Well defined camera shots









#### Hockey



#### Field End-Zone Activity



Increased Near-Field Visual Activity



#### Score Board Activity

Cut to Crowd Image

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Cut to Close-Up Image









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#### **Adding Text Sources**

- Leverage complementary textual sources:
  - Web sources: blogs, minute-by-minute match reports, commentary transcripts, ...
  - Domain knowledge base as ontological resource (event database, match metadata, etc)



- Objective:
  - Mine textual sources for specific types of events (as oppose to just "highlight")
  - Temporally align the text and AV results
  - Use the audio-visual detectors to characterise event types







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#### PhDs Never Had it So Good

- Iots of data means lots of interesting problems!
- Semantic gap means lots of exciting interdisciplinary papers and theses!
- PhDs get to watch The Simpsons as part of their research!
- PhDs get to watch lots of sports!





#### **Fictional Content**



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#### **Impose Event-based Structure**





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#### Impose Event-based Structure

 Define an event as temporal segment that viewers recognise and remember as a semantic unit.

- We work with three types of major events:
  - Dialogue, Exciting and "Montage".
- Account for 90% of a film, whilst being intuitive for a user to understand
- Studies indicate more intuitive than shots or scenes in a variety of retrieval applications









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#### Dialogue

- Usually carry most information about the plot, story, background
- Limited number of characters, significant shot repetition, predominantly speech, little camera motion or intra-shot activity
- Exciting
  - Very little shot repetition, significant camera motion, mixture of speech and music
- Montages
  - A superset of traditional montages (a juxtaposition of shots that typically spans both space and time), emotional events (romantic scene) and musical events (song and dance)





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#### **Event Classification in Movies**

#### Aim

- Detect meaningful sequences in movies
- Allow efficient user browsing
- Approach
  - Analyse filmmaking conventions
  - Apply knowledge to assist in detection
  - Develop feature detectors based on knowledge gained
  - Combine using Finite State Machines





#### **Dialog Events**



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- Viewers need to be relaxed in order to:
  - Concentrate
  - Understand
  - View acting
- Achieved through:
  - Clear views of characters
  - Relaxed shooting
  - Repetitive cut type
  - 180-degree line rule









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#### Ensure viewers engrossed in the action

- Create excitement
- Create tension
- Sense of uneasyness
- Achieved through
  - Fast paced editing
  - Continually bombarding viewer with new information
  - High amounts of motion







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#### Audio-Visual Detectors

#### Low-level feature analysis

- Audio: HZCR, short-term energy variation used to train SVMs for speech, music, quiet music and silence
- Video: shot boundary detection, shot clustering based on visual similarity, cluster-shot ratio, MPEG-7 motion features
- Multiple Finite State Machines running in parallel to detect potential sequences where features remain constant
- Use combinations of features to declare identified sequences as dialogues, exciting or montages
- E.g. % music, % speech, % static camera, motion intensity, shot length
- Can search on these individually for even finer grained access






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#### Demo 5: Film Browser

[Lehane B., O'Connor N.E., Lee H., Smeaton A.F., "Indexing Of Fictional Video Content For Event Detection And Summarisation", Journal of Image and Video Processing]





Exciting Montage Dialogue Film Name Prec. Prec. Prec. Recall Recall Recall 96% 17% 100% 95% American Beauty 86% 71% 84% 95% 96% Amores Perros 56% 56% 55% Battle Royal 62% 94% 71% 91% 72% 90% Chopper 90% 94% 22% 83% 50% 100% Dumb & Dumber 74% 91% 55% 100% 86% 68% Goodfellas 95% 90% 67% 60% 86% 46% 100% High Fidelity 80% 100% 17% 56% 83% Reservoir Dogs 89% 94% 50% 80%100% 100% 73% 97% 100% 67% 75% Shrek 58% 97% 100% Snatch 84% 71% 67% 83% 97% 100% 67% 100% 25%33% Sopranos 1 Sopranos 2 100% 100% 100% 96% 60% 75% Sopranos 3 77% 100% 38% 75% 75% 100% Simpsons 1 96% 100% 100% 100% Simpsons 2 89% 100% 100% 100% 100% 100% Simpsons 3 97% 67% 50% 100% 78% 81% 79% 100% 80%100% Lost 1 Lost 2 77% 94% 69% 100% 67% 100% 84% 78% 54% 100% 83% 100% Lost 3 81% 94% 59% 95% 73% 91% Average



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#### Adding Text-based Processing

#### Audio Description

- Describer relates essential details of the on-screen action
- Who is present, what they look like, what they are wearing, their facial expressions, and what they are doing.
- Inferring Characters onscreen presence
  - Detect re-occurring proper \_ nouns, followed by gender disambiguation, followed by pronoun resolution.
- Link characters and events based on temporal





00:45:25 Danny looks up and follows Russ across the warehouse.

00:45:44 They hover in the doorway. Danny paces.

00:46:03 Incredulous Russ looks away. He runs his fingers over his mouth.

00:46:23 They stare steadily at each other. A smile creeps across Danny's face. Russ turns away, folding his arms.

00:46:32 The two men nod gently at each other.

00:46:37 In the Bellagio Museum, Tess, wearing an oriental style suit, with a high collar stands serenely, gazing at a picture. The painting, in a rectangle frame, is Woman with Guitar by Pablo Picasso. Greys, browns and blues mingle in a cubist style. A short bald man chatters away beside Tess. A taller man joins them. They turn their heads as Benedict saunters in. Tess introduces him to the taller man, then Benedict, hands behind his back, studies the painting.





- → Within a film:
  - "Find exciting parts of the movie 'Road to Perdition' that contain Michael"
- Link character names to actors via www.imdb.com
  - "Find all dialogues featuring Humphrey Bogart and Lauren Bacall"

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# Character Relationships

	Lester	$\operatorname{Carolyn}$	Jane	Buddy	Angela	Ricky	Frank
Lester	1.00	0.40	0.43	0.09	0.36	0.38	0.21
$\operatorname{Carolyn}$	0.61	1.00	0.45	0.23	0.23	0.35	0.13
Jane	0.49	0.34	1.00	0.02	0.34	0.56	0.12
Buddy	0.57	1.00	0.14	1.00	0.00	0.14	0.14
Angela	0.71	0.29	0.58	0.00	1.00	0.54	0.29
Ricky	0.46	0.28	0.59	0.03	0.33	1.00	0.41
Frank	0.56	0.22	0.28	0.06	0.39	0.89	1.00







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# PhDs Never Had it So Good

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#### Where next?



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# Change the Capture Paradigm

- Extracting semantics from a 2D array of pixels is hard!
- How can we make life easier?
- Design capture devices that make the problem easier ...
- Augment visual sensor with other modalities
- Examples:
  - Multiple cameras (e.g. stereo)
  - Beyond the visible spectrum (e.g. infrared)
  - Non-content sensors: time, date, location, movement, ...





# Demo 6: MediAssist





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# Demo 7: SenseCam



[Byrne et al, Using Bluetooth and GPS Metadata to Measure Event Similarity in SenseCam Images, IMAI 2007]





# Demo 8: Pedestrian detection and tracking

[Kelly et al, Pedestrian Detection using Stereo and Biometric Information, ICIAR 2006]



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# Demo 9: Combined visible/IR object tracking

[O'Conaire et al, Thermo-Visual Feature Fusion for Object Tracking Using Multiple Spatiogram Trackers, Machine Vision and Applications, 2007]





Conclusion

- Examples of some audio and visual features for CBIR provided
  - There are many more being defined all the time
  - Good place to start for a standardised set is ISO/IEC Content Description Interface AKA "MPEG-7"
  - Defines features in terms of:
    - How output is represented in XML-like syntax
    - Recommendation for how to extract the feature
    - Recommendation for how to calculate feature distance







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# Conclusion

- The real challenge now is not to define, extract and match features ....
- ... but in determining how features can be combined for tasks such as:
  - Content structuring (e.g. summarisation)
  - Event detection
  - Scene classification
  - Concept detection
  - Object and activity recognition
  - Multi-modal retrieval





# Conclusion

- Unfortunately there is a problem the Semantic Gap:
  - "the large disparity between the low-level features or content descriptors that can be computed automatically and the richness and subjectivity of semantics in user queries and high-level human interpretations of audiovisual media"

[K-Space Network of Excellence]

- Problem facing the research community for many years to come
- Requires integration of research efforts from many different areas:
  - AV analysis, IR, semantic web, personalisation, GUI design, ...
- That's why you're at SSMS!









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# PhDs Never Had it So Good

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- PhDs get to watch lots of sports!
- PhDs get to watch lots on movies!
- PhDs get to go to Crete for a week!







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#### PhDs Never Had it So Good

Iots of data means lots of interesting problems!

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# PhDs Never Had it So Good

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#### Thanks for your attention!

# **Questions & Follow-up**

# Noel.OConnor@dcu.ie







# **Appendix A - Texture**

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# **Appendix A - Texture**

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# **Appendix A - Texture**







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