Video Object Mining : Issues and Perspectives

Jonathan Weber, Sébastien Lefèvre, Pierre Gançarski

LSIIT, University of Strasbourg Ready Business System

September 23, 2010











High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent

High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent

High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent

High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

How can we mine efficiently these complex data ?

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent

High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

How can we mine efficiently these complex data ?

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent

High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

How can we mine efficiently these complex data ?

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent

High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

How can we mine efficiently these complex data ?

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent

High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

How can we mine efficiently these complex data ?

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent

High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

How can we mine efficiently these complex data ?

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent
- \implies Lack of semantic information

High quantity of video data

- Low cost digital camera
- High storage capacity
- High-speed internet
- Ex : YouTube, Dailymotion, ...

How can we mine efficiently these complex data ?

User needs content-based tools but

- Video meta-data are not sufficient
- Manual tagging of video is time consuming and error-prone
- There is a semantic gap between video data and what they represent
- \implies Lack of semantic information

How can we introduce semantic in the mining process ?



2 Survey of video mining systems

3 Perspectives: Video Object Mining



Video Mining

 Process of extracting information/knowledge from large amounts of video data

Many recent publications deal with video mining:

- A. Anjulan and N. Canagarajah, Signal Processing: Image Communication, 2007
- A. Anjulan and N. Canagarajah, IEEE ICIP, 2007
- S. de Avila, A. da Luz, and A. de Araujo, IWSSIP, 2008
- A. Basharat, Y. Zhai, and M. Shah, Computer Vision and Image Understanding, 2008
- F. Chevalier, J.-P. Domenger, J. Benois-Pineau, and M. Delest, Pattern Recognition Letters, 2007
- X. Gao, X. Li, J. Feng, and D. Tao, Pattern Recognition Letters, 2009
- D. Liu and T. Chen, Computer Vision and Image Understanding, 2009
- W. Ren and Y. Zhu, IIH-MSP, 2008
- J. Sivic and A. Zisserman, Proceedings of the IEEE, 2008
- L. F. Teixeira and L. Corte-Real, Pattern Recognition Letters, 2009
- S. Zhai, B. Luo, J. Tang, and C.-Y. Zhang, ICIG, 2007

Study of existing systems

- Characterize the different systems
- Check if they use semantics

Video Mining

- Process of extracting information/knowledge from large amounts of video data
- Many recent publications deal with video mining:
 - A. Anjulan and N. Canagarajah, Signal Processing: Image Communication, 2007
 - A. Anjulan and N. Canagarajah, IEEE ICIP, 2007
 - S. de Avila, A. da Luz, and A. de Araujo, IWSSIP, 2008
 - A. Basharat, Y. Zhai, and M. Shah, Computer Vision and Image Understanding, 2008
 - F. Chevalier, J.-P. Domenger, J. Benois-Pineau, and M. Delest, Pattern Recognition Letters, 2007
 - X. Gao, X. Li, J. Feng, and D. Tao, Pattern Recognition Letters, 2009
 - D. Liu and T. Chen, Computer Vision and Image Understanding, 2009
 - W. Ren and Y. Zhu, IIH-MSP, 2008
 - J. Sivic and A. Zisserman, Proceedings of the IEEE, 2008
 - L. F. Teixeira and L. Corte-Real, Pattern Recognition Letters, 2009
 - S. Zhai, B. Luo, J. Tang, and C.-Y. Zhang, ICIG, 2007

Study of existing systems

- Characterize the different systems
- Check if they use semantics

Video Mining

- Process of extracting information/knowledge from large amounts of video data
- Many recent publications deal with video mining:
 - A. Anjulan and N. Canagarajah, Signal Processing: Image Communication, 2007
 - A. Anjulan and N. Canagarajah, IEEE ICIP, 2007
 - S. de Avila, A. da Luz, and A. de Araujo, IWSSIP, 2008
 - A. Basharat, Y. Zhai, and M. Shah, Computer Vision and Image Understanding, 2008
 - F. Chevalier, J.-P. Domenger, J. Benois-Pineau, and M. Delest, Pattern Recognition Letters, 2007
 - X. Gao, X. Li, J. Feng, and D. Tao, Pattern Recognition Letters, 2009
 - D. Liu and T. Chen, Computer Vision and Image Understanding, 2009
 - W. Ren and Y. Zhu, IIH-MSP, 2008
 - J. Sivic and A. Zisserman, Proceedings of the IEEE, 2008
 - L. F. Teixeira and L. Corte-Real, Pattern Recognition Letters, 2009
 - S. Zhai, B. Luo, J. Tang, and C.-Y. Zhang, ICIG, 2007

Study of existing systems

- Characterize the different systems
- Check if they use semantics

Video Mining

- Process of extracting information/knowledge from large amounts of video data
- Many recent publications deal with video mining:
 - A. Anjulan and N. Canagarajah, Signal Processing: Image Communication, 2007
 - A. Anjulan and N. Canagarajah, IEEE ICIP, 2007
 - S. de Avila, A. da Luz, and A. de Araujo, IWSSIP, 2008
 - A. Basharat, Y. Zhai, and M. Shah, Computer Vision and Image Understanding, 2008
 - F. Chevalier, J.-P. Domenger, J. Benois-Pineau, and M. Delest, Pattern Recognition Letters, 2007
 - X. Gao, X. Li, J. Feng, and D. Tao, Pattern Recognition Letters, 2009
 - D. Liu and T. Chen, Computer Vision and Image Understanding, 2009
 - W. Ren and Y. Zhu, IIH-MSP, 2008
 - J. Sivic and A. Zisserman, Proceedings of the IEEE, 2008
 - L. F. Teixeira and L. Corte-Real, Pattern Recognition Letters, 2009
 - S. Zhai, B. Luo, J. Tang, and C.-Y. Zhang, ICIG, 2007

Study of existing systems

- Characterize the different systems
- Check if they use semantics

- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels

Summarization

- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels





Properties

- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels

Classification



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels

- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



Properties

Objectives

- Elements
- Descriptors
- Scales
- Supervision levels



Properties

Objectives

- Elements
- Descriptors
- Scales
- Supervision levels



Properties

Objectives

- Elements
- Descriptors
- Scales
- Supervision levels



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels

Properties Objectives Elements Descriptors Scales Supervision levels











- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels

- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels



Semi-Supervised

- Objectives
- Elements
- Descriptors
- Scales
- Supervision levels





Objectives

Elements

Descriptors

Scales

Supervision



Elements

Descriptors

Scales

Supervision



Descriptors

Scales

Supervision



Scales

Supervision



Supervision





2 Survey of video mining systems



4 Conclusion



- Generic framework
- Object is the most semantic element
- Combination of object-oriented descriptors
- 2 types of scales : inner and context scale
- User relevance feedback brings semantics



- Generic framework
- Object is the most semantic element
- Combination of object-oriented descriptors
- 2 types of scales : inner and context scale
- User relevance feedback brings semantics



- Generic framework
- Object is the most semantic element
- Combination of object-oriented descriptors
- 2 types of scales : inner and context scale
- User relevance feedback brings semantics



- Generic framework
- Object is the most semantic element
- Combination of object-oriented descriptors
- 2 types of scales : inner and context scale
- User relevance feedback brings semantics



- Generic framework
- Object is the most semantic element
- Combination of object-oriented descriptors
- 2 types of scales : inner and context scale
- User relevance feedback brings semantics



- Generic framework
- Object is the most semantic element
- Combination of object-oriented descriptors
- 2 types of scales : inner and context scale
- User relevance feedback brings semantics

Our approach compared to related works



Conclusion





Conclusion



Conclusion



Conclusion



Conclusion



Conclusion



Conclusion



Conclusion



Conclusion

VOMF: Video Object Mining Framework





- 2 Survey of video mining systems
- 3 Perspectives: Video Object Mining



Issues

- Massive video repositories need new data mining schemes
- Semantics have to be considered to achieve user goals
- These are still open problems

Perspectives

- Video Object Mining has to be explored
- Semi-supervised learning limits user's workload
- A new generic framework has been proposed
- This framework is currently being implemented

Difficulties

- Object segmentation
- Interactive mining (involving user relevance feedback)

Issues

- Massive video repositories need new data mining schemes
- Semantics have to be considered to achieve user goals
- These are still open problems

Perspectives

- Video Object Mining has to be explored
- Semi-supervised learning limits user's workload
- A new generic framework has been proposed
- This framework is currently being implemented

Difficulties

- Object segmentation
- Interactive mining (involving user relevance feedback)

Issues

- Massive video repositories need new data mining schemes
- Semantics have to be considered to achieve user goals
- These are still open problems

Perspectives

- Video Object Mining has to be explored
- Semi-supervised learning limits user's workload
- A new generic framework has been proposed
- This framework is currently being implemented

Difficulties

- Object segmentation
- Interactive mining (involving user relevance feedback)

Issues

- Massive video repositories need new data mining schemes
- Semantics have to be considered to achieve user goals
- These are still open problems

Perspectives

- Video Object Mining has to be explored
- Semi-supervised learning limits user's workload
- A new generic framework has been proposed
- This framework is currently being implemented

Difficulties

- Object segmentation
- Interactive mining (involving user relevance feedback)