Lossless Video Compression Technique Using Bayesian Network and Entropy Coding

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Outline

1. Motivation
2. Methodology
3. Experiments
4. Analysis
Global Internet Protocol video traffic will grow four-folds from 2017 to 2022\(^1\)

UHD (or 4K) video will account for 22 percent of global IP Video traffic by 2022\(^1\)

IP video traffic will account for 82 percent of traffic by 2022\(^1\)

**High Fidelity** video data is playing an *increasingly* important role in *medicine, science, education, and entertainment*

**Lossless** video compression algorithms are used in applications ranging from *archival of video records* to the *field of medicine*

\(^1\)Cisco Visual Networking Index: *Forecast and Trends, 2017–2022, Updated: February 27, 2019*
Video Compression

Pattern Recognition & Pattern Classification

- Spatial Correlation - Intra frame
- Temporal Correlation - Inter frame
- Encoding Schemes
Model and Update beliefs about states of certain variables when some other variables were observed

BNs aim to model conditional dependence between variable states

Given a BN, the Joint Probability distribution over all variables $x_1, ..., x_n$ is then calculated as:

$$P(x_1, \cdots, x_n) = \prod_{i=0}^{n} P(x_i | \prod_{i=0}^{n} x_i)$$  \hspace{1cm} (1)
BN Structure Learning

• Given a dataset of values, motivation is to discover a BN structure that best represents the data

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Algorithm 1 Structure Learning

function GreedyHillClimbing(initial structure, \( N_{init} \), dataset \( D \), scoring function \( s \), stopping criteria \( C \))

\( N^* \leftarrow N_{init}, N' \leftarrow N^*, \text{tabu} \leftarrow N^* \)

while \( C \) is not satisfied do

\( N'' \leftarrow \text{argmax}_{N \in \text{neighborhood}(N')} \text{and} N \notin \text{tabu} \) \( s(N) \)

if \( s(N') > s(N'') \) then // Check local optimum

\( N'' \leftarrow \text{random}(N') \) // Random operators

end if

if \( s(N'') > s(N^*) \) then // Check new best

\( N^* \leftarrow N'' \)

end if

\( \text{tabu} \leftarrow \text{tabu} \cup N' \)

\( N' \leftarrow N'' \) // Move to neighbor

end while

return \( N^* \)

end function
```
Problem Statement

Bayesian Networks for Video Compression ?!
Color Space Conversion

\[ Y = \frac{77}{256} R + \frac{150}{256} G + \frac{29}{256} B \]

\[ C_b = -\frac{44}{256} R - \frac{87}{256} G + \frac{131}{256} B + 128 \]

\[ C_r = \frac{131}{256} R - \frac{110}{256} G - \frac{21}{256} B + 128 \]

Difference Coding

(a) Difference

Binary Code

(a) Binary Codes
Learning a Bayesian Network

- Model conditional dependencies between individual binary variables by learning a BN structure.
- Choose the network with least Bayesian Information Criterion (BIC) score either by hill-climbing (HC) or a Tabu search (TABU) greedy search.

(a) Bayesian Network
Huffman Encoding

- Compute JP from Conditional Probability (CP) Table
- Construct a Huffman Encoding tree
- Look-up table will be based on CP rather than JP or frequency
Putting it all together...

Diagram:

1. Raw Digital Video
2. Raw Video Framing
3. YCbCr Decomposition
4. Pixel Transformation
5. Binary Code Construction
6. Learning Bayesian Networks
7. Entropy Encoding

Flow:
- Chroma & Luma Processing
- Compressed Video
Experimental Setup

- Raw uncompressed video files selected from SVT High Definition Multi-Format Test Set
- Compared the proposed technique *BayesianCompress* with *Gzip*, *FFV1*, *H.264* or *MPEG-4 Part 10*, *Dirac* and *JPEG2000*
- Pixel Transformation and Entropy Coding implemented in C programming language, compiled using the GNU C Compiler (GCC)
- Structure Learning of the Bayesian Network was implemented using *bnlearn* and *gRain* packages in R programming language
### Results

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<thead>
<tr>
<th>Parameter</th>
<th>blue_sky</th>
<th>rush_hour</th>
<th>station</th>
<th>tractor</th>
<th>Avg. Ratio (25 fps)</th>
<th>crowd_run</th>
<th>into_tree</th>
<th>old_town</th>
<th>Avg. Ratio (50 fps)</th>
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</thead>
<tbody>
<tr>
<td>Frame Rate (fps)</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>-</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>-</td>
</tr>
<tr>
<td># of Frames</td>
<td>217</td>
<td>500</td>
<td>313</td>
<td>690</td>
<td>-</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>-</td>
</tr>
<tr>
<td>Codec</td>
<td>Gzip</td>
<td>FFV1</td>
<td>H.264</td>
<td>Dirac</td>
<td>JPEG2000</td>
<td>BayesianCompress</td>
<td></td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Codec</th>
<th>Compression Ratio</th>
</tr>
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<tbody>
<tr>
<td>Gzip</td>
<td>1.85 2.03 1.90 1.67</td>
</tr>
<tr>
<td>FFV1</td>
<td>2.74 3.19 2.69 2.74</td>
</tr>
<tr>
<td>H.264</td>
<td>2.68 3.04 2.69 2.65</td>
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<tr>
<td>Dirac</td>
<td>2.67 2.90 2.68 2.56</td>
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<tr>
<td>JPEG2000</td>
<td>2.62 3.20 2.69 2.73</td>
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<tr>
<td>BayesianCompress</td>
<td>2.69 3.13 2.80 2.88</td>
</tr>
</tbody>
</table>
Correlation and Conditional Dependencies of Pixels in independent Color Axis of a video stream can be exploited using Bayesian Networks for Video Compression.

Performed on average better than state-of-the-art techniques @ 25 fps, slightly behind H.264 @ 50 fps.

Exploring the use of Arithmetic Coding.

Custom Bayesian Network learning algorithm specifically for the proposed video compression technique to improve its overall accuracy and improve performance.
References I


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Differential Pulse Code Modulation (DPCM), [http://einstein.informatik.uni-oldenburg.de/rechnernetze/dpcm.htm](http://einstein.informatik.uni-oldenburg.de/rechnernetze/dpcm.htm)

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Tony Robinson, SHORTEN: Simple lossless and near lossless waveform compression

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John Skilling. *Nested Sampling for General Bayesian Computation*

Q&A
Thank You!