

DOES INFORMATION DENSITY OF TELEVISION PROGRAMS INCREASE OVER TIME?

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Abstract

This paper describes the concept of information density from the video content perspective, and points out the potential problem of information overload that is rarely mentioned in the context of that media. Presented is the possibility of using algorithms for registration of movement with the aim of quantitative analysis of information density of a given video content, a using a single simple algorithm, MTV Music Awards winner videos in the category VIDEO OF THE YEAR for the past 30 years have been analyzed. In this sample, an increase in information density has been observed, and that phenomenon, which is ignored because much more focus is given to the qualitative analysis of the content of the video material, is pointed out.

Key words: *information density, information overload, television, video*

1. INTRODUCTION

Time spent watching television programs is increasing. Market researches indicate that citizens of the United States spend an average of 34 hours and 39 minutes a week in front of the television screen. Individuals over 65 years of age spend the most time in front of the screen, and their viewing hours amount is over 47 hours a week, while youth spend the least time in front of the screen and their viewing hours amount is 23 hours and 41 minute a week (group between 12 and 18 years) [Nielsen, 2011]. With the development of technology, ways of watching television programs have somewhat changed, especially among the younger population. Rideout et al. also point to the constant increase in the time spent watching television program in the population between 8 and 18 years, emphasizing that in 1999 that population spend an average of 3 hours and 47 minutes a day watching television, which has increased to 4 hours and 29 minutes by 2009. There is an increasing trend of watching television via the Internet, iPods and mobile phones. The authors also mention the fact that 71% of respondents have a TV set in the room they sleep in [Rideout et al., 2010]. It should be emphasized that the abovementioned authors under the term "watching television program" consider watching various video content, from classic TV programs, television on demand and even watching DVD movies.

Since people spend a lot of time watching television programs, and since their influence on the attitudes and behavior is not negligible, a number of studies have been published on that topic. Special attention is paid to the impact of media on young people, and numerous researches have been conducted in that area. Some authors have analyzed the impact of time spent in front of television screens on obesity among preschool children and indicated that there is a connection between these two variables [Lumeng et al., 2006]. Other authors have pointed out the existence of a negative relation between time spent watching television programs among three-year-olds and their results on cognitive abilities test when they reached the age of 6 and 7 years [Zimmerman et al. 2005]. In addition, it has been discovered that there is a connection between the time spent watching television among children 1 and 3 years of age and later attention disorders among those children when they reach the age of 7 years [Christakis et al. 2004]. Zimmerman notes that some papers indicate that watching television programs has an impact on the quality of sleep in children due to a delay of secretion of melatonin hormone whose secretion is interfered by the exposure to radiation emanating from television screens [Zimmerman 2008]. The same author claims that there are numerous unanswered questions in the area of influence of the media on youth and the research in that area is continuing.

Regulated societies have introduced mechanisms for controlling the content of television programs that are watched by children and youth. Some states have institutions whose task is to assess the acceptability of certain movies and other forms of video materials to viewers according to their age. One example is Portugal where movies, videos, DVDs, digital games and theatrical performances are categorized. Content is categorized into five categories based on the age: 4, 6, 12, 16 and 18. In addition, there are also special categories (pornography and quality) that are cumulatively added to the above mentioned categories [CCE, 2006]. In the UK, the classification categories are U, PG, 12, 12A, 15, 18 and R18. The numbers refer to the age of the viewer, while U symbol indicated that there are no restrictions, and PG designation indicates that the content should be acceptable to children age eight and older. [BBFC, 2014]. However, common to all control systems is that they deal with content in a way that the same is not broadcasted to ages for which it is estimated that such content would be disturbing or that viewers of that age would not comprehend the content.

On the other hand, there is a realization that video materials also have other properties that can affect the viewers, and such are not covered by these systems of content control. Friedrich and Stein have quite a long time ago pointed out that the video content which children are exposed to, and which alternates faster, can make children more impulsive, while the content that alternates slowly can make children more persistent in solving school tasks [Friedrich & Stein, 1973]. Cooper et al. concluded that the authors are mostly concerned with the time spent watching video contents, while they focused on the impact of scene alternation speed on certain abilities of the children. The study used an ANT aptitude test developed by Fen et al. [Fen et al., 2002], which measures attention and orientation. Before testing, they showed to children between age 4 and 7 videos in which the narrator tells a tale in less than 4 minutes. The only difference was that one group of children watched a clip in which the scenes alternated every four seconds, while the other group watched the same video but with scene alternation approximately every twenty seconds. Contrary to their expectation, they found that children to whom a slower version was shown made more errors in the ATP test than children who had been watching faster version [Cooper et al., 2009]. Apart from the abovementioned researches regarding the speed of scene alteration, some authors have tried to analyze the amount of activity in video contents. Canini et al. found that a variable that represents a combination of activity in certain scenes and scene alteration speed has positive correlation with the level of skin conductance of respondents who are watching the scene [Canini et al., 2010].

The aforementioned papers have primarily suggested to the constant growth of time spent in front of television screens, as well as the significant impact of the media on the population. Previously, a border between the quality control of television program that is performed in regulated societies and the quantity in terms of the amount of information that a television program contains has been defined. The paper itself deal with that other, often neglected, feature of video material which has only lately received more attention. That feature is quantity of information in a video content, which can be called information density.

2. INFORMATION DENSITY AND OVERLOADING

The very term "information density" is used in many different fields and therefore has variable meaning, although it is generally associated with the quantity of information and the surface or an area in which they are stored, and higher density means that more information is stored in a given area or space. Firstly, all fields in which this term is used will be listed, while further in the paper an explanation will be given regarding which "information density" will be used for the purposes of this paper.

One of the fields in which "information density" is often mentioned is certainly data storage, so this term is seen in the title of the patent by Keirn and Woods titled Technique for increasing information density in data storage devices by utilizing a high-efficiency encoding scheme [Keirn et al., 1998]. Information density is a term used also for devices for displaying information such as LCD matrix, for example in the paper by Schadt et al. (New Liquid Crystal Materials, Physical Properties and Performance in Displays for cars, High Density Information and Guest-Host Applications) [Schadt, et

al., 1983]. The same concept is seen in the field of chemistry where authors mention it in a paper on DNA nanostructures (Addressable high-information-density DNA nanostructures) [Tumpane et al., 2007], and is also mentioned in the field of communications in terms of information density optimization through syntactic reduction (Speakers optimize information density through syntactic reduction) [Scholkopf et al., 2007].

The sense in which this term is used in the remainder of this paper is closest to how authors Lang et al. use it in their research, who defined this term as a numerical variable that expresses the number of introduced information in seconds [Lang et al., 2007]. The context in which the authors define the concept of video content broadcasting, i.e. television program. A more detailed elaboration of the density of information as a numeric variable can be found in a different paper where the author describes the need for a new variable, i.e. a measure which would precisely define the amount of information that is broadcast through video content. To achieve this, a new variable, which is abbreviated as I^2 is composed of seven dimensions. These are: Object Change, Novelty, Relatedness, Distance, Perspective, Emotion and Form change. The author and colleagues in their paper use the specified variable with the aim of upgrading their communication theory called The Limited Capacity Model of Mediated Message Processing (abbreviation LC4MP) through they have proven in several of their papers using STRT (secondary task reaction time) methodology [Lang, 2000]. The theory and the methodology used are based on the limited capacity models of attention which implies that human beings process information and that such processing requires mental resources [Navon & Gopher, 1979; Schneide et al., 1984]. According to Lang, information processing consists of three sub-processes, namely:

- a) Encoding
- b) Storage
- c) retrieval

and two mechanisms:

- I) orienting behavior
- II) resource allocation

Resource allocation is a key mechanism in which the limited cognitive resources are allocated to the aforementioned sub-processes. LC4MP theory has offered an explanation for the anomaly that occurred in certain situations when the aforementioned STRT test has been applied, and the theory itself introduces several new concepts, namely:

- a) total resources - overall cognitive resources of an individual
- b) allocated resources - resources that are currently available for processing
- c) resources required - resources that are required for processing
- d) resources remaining - the difference between total and resources required
- e) resources available - the difference between allocated resources and resources required

Description of the theory and all its elements is beyond the scope of this paper, and a few key assumptions include the limitation of total cognitive resources of a person who is exposed to a source of information, and of the total resources only certain quantity, which should be sufficient for processing, is allocated. Allocated resources are usually dependent on the interest of people for information. If necessary, there is a reallocation, and the upper limit of resources that can be allocated exists and it can be reached. The question that remains is what if we are constantly exposed to such a quantity of information that the required resources are equal to or greater than the total resources? One answer to this question is the concept of information overloading, but that is completely separate field of research [Lang et al., 2007].

Information overloading as a concept has been introduced by sociologists, so Simmel more than one hundred years ago stated that "overload of sensations in the modern urban world caused city dwellers to become jaded and interfered with their ability to react to new situations" [Bomman et.al., 2003]. Interestingly, the term information overload was initially a subject of debate, and some authors disputed the existence of it, so Tidline argues that it is a myth [Tidline, 1999], although few question about its existence remain today. The term information overloading is today commonly associated

with the Internet, and Heylighen describes it as follows: "People find it ever more difficult to cope with all the new information they receive, constant changes in the organizations and technologies they use, and increasingly complex and unpredictable side-effects of their actions." [Heylighen, 2002]. It is interesting that this term is mentioned in various fields of science, and Akin in his overview of overall scientific literature from the period between 1960 and 1996 mostly saw this term in the fields of literature, psychology and marketing [Akin, 1997].

Let us look at the term information density again from another angle. Authors Lang et al. have proposed a numerical variable for defining information density of the emitted video content, although it is based on qualitative assessments of skilled and trained assessors [Lang et al., 2007]. The idea of this paper is an attempt to use fully quantitative algorithms that exclude activity and assessment by the people as a means of defining information density. In the last decade there has been a rapid development of video surveillance equipment, and algorithms for detecting movement of people, vehicles etc. have simultaneously been developed. These algorithms could be used for measuring information density, which would result in numerical values that are completely devoid of subjectivity. Below is an overview of some algorithms for registering movement.

3. ALGORITHMS FOR REGISTRATION OF CHANGE

The basic principle that algorithms for registration of movement in video content use consists of comparing each frame with the previous and finding differences between them. If we have a video recording without any movement, it is clear that there will be no difference between the frames. On the other hand, if the video contains any movement, some frames will vary and only in areas where the movement occurred. From this it is clear that the mere detection of movement is not a big problem for the algorithms, but their complexity grows with additional capabilities. Additional features that have been implemented in more advanced algorithms are commonly used for removing the influence of some natural phenomena on motion detection. That usually includes precipitation (rain or snow) or slight movement of the leaves in the wind, which simpler algorithms register as a movement, and in video surveillance such movements should be ignored.

One of the simplest approaches to registering movement that will be used in this paper consists of a comparison of adjacent frames, at the level of each pixel, and in the case that the same pixel varies in two adjacent frames above the defined threshold, movement is registered at the pixel. Since video materials are typically in color, better results are obtained by comparing each pixel color component (RED, GREEN, BLUE), while the second approach is that the videos are converted to black and white with different shades of gray, and then only one value per pixel is compared. Described method is generally not used in video surveillance systems, because it has a number of disadvantages. First of all, there is already described problem of detection of rainfall, which is registered as a movement, as well as already mentioned impact of wind that can cause false positives or repetitive movement of objects (for example, leaves) or vibration of the camera. Furthermore, if change is lightning occurs caused by sun being blocked by the clouds and then reappearing, you get a false detection of movement.

In order to overcome these problems, more advanced algorithms have been developed that are used in video surveillance systems. One of the most famous was proposed by Horprasert et al., and one of its properties is its efficiency in problems of overshadowing [Horprasert et al., 2000]. The second used algorithm was developed by Stauffer and Grimson, and among other things it is quite efficient in distinguishing repeated movements from rectilinear movements [Stauffer et al., 1999]. The development of algorithms is continuing, and more and more we see algorithms for special purposes. One example is an algorithm for detecting flames, for which there is also an interest, and such algorithms are currently being developed [Yu et al., 2013].

4. RESEARCH METHODS

This paper uses the simplest algorithm for detecting movement which is briefly described in the previous section, and as a result of the algorithm with a given threshold, it also provides information on a percentage of pixels that have changed above the specified threshold for each pair of adjacent frames. The assumption is that the change of pixel color is a result of movement, i.e. the change between two frames. The algorithm functions according to flow diagram presented in Figure 1.

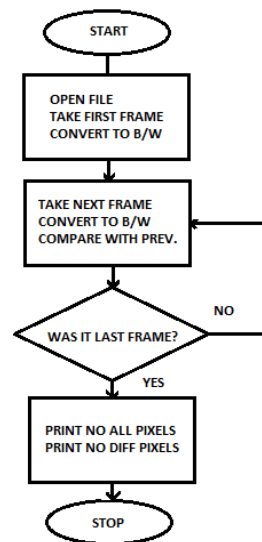


Figure 1 - Flow diagram of the algorithm

The functional principle is given in the following example. Assuming that the video has 5 frames, and the video resolution is 100 pixels horizontally and 100 pixels vertically. Each frame in this case has 10,000 pixels, and a total of four comparisons are performed during the processing (1-2, 2-3, 3-4 and 4-5). Since in black and white frames each pixel can take any value from 0 to 255 (0 is black, 255 is white), in each comparison two numbers are compared where each number represents a shade of gray at the same location within the frame, but in different frame. If the pixels differ more than a given threshold, a counter which detects changes in the pixels with respect to the previous frame is incremented. The higher the number of changed pixels with respect to the previous frames, more significant changes in the video occurred, and we can assume that information density is higher. This algorithm has a number of shortcomings, but in this case they will be ignored.

Video contents that have been analyzed with the algorithm are the winners of MTV Music Awards which received VIDEO OF THE YEAR award during the past 30 years. All videos are available on www.youtube.com website from which they have been downloaded using Youtube downloader tool. List of videos included, year, artist, song name and a hyperlink to processed video can be found in the following three tables.

YEAR	VIDEO OF THE YEAR WINNER	SONG	HYPERLINK
1984	The Cars	"You Might Think"	http://www.youtube.com/watch?v=3dOx510kyOs
1985	Don Henley	"The Boys of Summer"	http://www.youtube.com/watch?v=qh4nVj8g4hg
1986	Dire Straits	"Money for Nothing"	http://www.youtube.com/watch?v=wTP2RUD_cL0
1987	Peter Gabriel	"Sledgehammer"	http://www.youtube.com/watch?v=NR6pyJy--MQ
1988	INXS	"Need You Tonight/Mediate"	http://www.youtube.com/watch?v=Mg9mlMnQAVM
1989	Neil Young	"This Note's for You"	http://www.youtube.com/watch?v=KSSvzCNBvIQ
1990	Sinéad O'Connor	"Nothing Compares 2 U"	http://www.youtube.com/watch?v=iUiTQvT0W_0
1991	R.E.M.	"Losing My Religion"	http://www.youtube.com/watch?v=xwtdhWltSIg
1992	Van Halen	"Right Now"	http://www.youtube.com/watch?v=YCCLNmOpN3A
1993	Pearl Jam	"Jeremy"	http://www.youtube.com/watch?v=MS91knuzoOA

Table 1: Video of the year winners 1984 – 1993

YEAR	VIDEO OF THE YEAR WINNER	SONG	HYPERLINK
1994	Aerosmith	"Cryin'"	http://www.youtube.com/watch?v=qfNmyxV2Ncw
1995	TLC	"Waterfalls"	http://www.youtube.com/watch?v=8WEtxJ4-sh4
1996	The Smashing Pumpkins	"Tonight, Tonight"	http://www.youtube.com/watch?v=NOG3eus4ZSo
1997	Jamiroquai	"Virtual Insanity"	http://www.youtube.com/watch?v=MEyXHTQ_xV8
1998	Madonna	"Ray of Light"	http://www.youtube.com/watch?v=fLkNJYG4b2Q
1999	Lauryn Hill	"Doo Wop (That Thing)"	http://www.youtube.com/watch?v=T6QKqFPRZSA
2000	Eminem	"The Real Slim Shady"	http://www.youtube.com/watch?v=FhdHQ1wGSas
2001	Christina Aguilera, Lil' Kim, Mýa and Pink	"Lady Marmalade"	http://www.youtube.com/watch?v=RQa7SvVCdZk
2002	Eminem	"Without Me"	http://www.youtube.com/watch?v=YVkuVmdQ3HY
2003	Missy Elliott	"Work It"	http://www.youtube.com/watch?v=VsRk3dhbpKw

Table 2: Video of the year winners 1994 - 2003

YEAR	VIDEO OF THE YEAR WINNER	SONG	HYPERLINK
2004	OutKast	"Hey Ya!"	http://www.youtube.com/watch?v=PWgvGjAhvIw
2005	Green Day	"Boulevard of Broken Dreams"	http://www.youtube.com/watch?v=Soa3gO7tL-c
2006	Panic! at the Disco	"I Write Sins Not Tragedies"	http://www.youtube.com/watch?v=vc6vs-l5dkc
2007	Rihanna (featuring Jay-Z)	„Umbrella“	http://www.youtube.com/watch?v=CvBfHwUxHlk
2008	Britney Spears	"Piece of Me"	http://www.youtube.com/watch?v=KmN_NtMkBbg
2009	Beyoncé	"Single Ladies (Put a Ring on It)"	http://www.youtube.com/watch?v=4m1EFMoRFvY
2010	Lady Gaga	"Bad Romance"	http://www.youtube.com/watch?v=qrO4YZeylOI
2011	Katy Perry	"Firework"	http://www.youtube.com/watch?v=QGJuMBdaqIw
2012	Rihanna (featuring Calvin Harris)	„We Found Love“	http://www.youtube.com/watch?v=tg00YEETFzg
2013	Justin Timberlake	"Mirrors"	http://www.youtube.com/watch?v=uuZE_IRwLNI

Table 3: Video of the year winners 2004 – 2013

The algorithm has been implemented in Python programming language version 2.7.6. and OpenCV library has been used for processing. The appearance of the screen during processing is shown in Figure 2 where three open windows containing video content are seen where one window contains original video (window b), while the other window shows the difference between two frames expressed as a shade of gray (window c). The bigger the difference, the brighter the color representing that pixel becomes. In the third window we see white surface on which current and previous frame differ above the predefined threshold (window a). Threshold is included in the program itself and amounts to 10, which is slightly below 4% of the maximum value of 255.

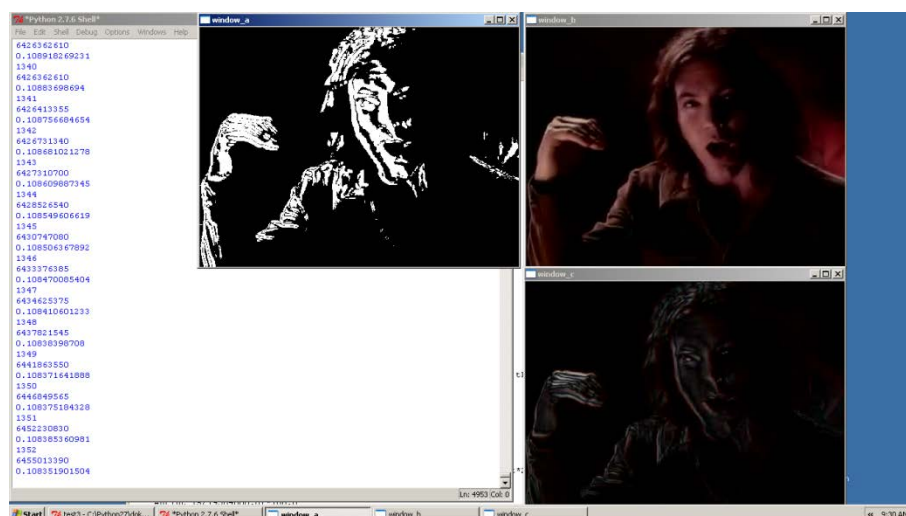


Figure 2: Video processing in Python

Implementation of the algorithm in python programming language is below.

```
import cv2
import random
import numpy as np
brojframeova=0
ukupanzbrojbijelih=0
konacaniznos=0.0
s=0.0
# Create windows to show the captured images
cv2.namedWindow("window_a", cv2.CV_WINDOW_AUTOSIZE)
cv2.namedWindow("window_b", cv2.CV_WINDOW_AUTOSIZE)
cv2.namedWindow("window_c", cv2.CV_WINDOW_AUTOSIZE)
capture = cv2.VideoCapture('2013s.avi')
#dimensions
frameWidth = capture.get(cv2.cv.CV_CAP_PROP_FRAME_WIDTH)
frameHeight = capture.get(cv2.cv.CV_CAP_PROP_FRAME_HEIGHT)
flag,current = capture.read()
flag,previous = capture.read()

while True:
    previous = current
    flag,current = capture.read()
    difference = cv2.absdiff(current, previous) #difference is taken of the current frame and the
previous frame
    frame2 = cv2.cvtColor(difference, cv2.cv.CV_RGB2GRAY)
    retval,thresh = cv2.threshold(frame2, 10, 255, cv2.THRESH_BINARY)
    cv2.imshow('window_a', thresh)
    cv2.imshow('window_b', current)
    cv2.imshow('window_c', difference)
    brojframeova=brojframeova+1
    s=thresh.sum()
    ukupanzbrojbijelih=ukupanzbrojbijelih+s
    konacaniznos=ukupanzbrojbijelih/(brojframeova*frameWidth*frameHeight*255)
    print brojframeova
    print ukupanzbrojbijelih
    print konacaniznos
    previous = current
    key = cv2.waitKey(10) #20
    if key == 27: #exit on ESC
        cv2.destroyAllWindows()
        break
```

5. RESULTS

Tables below contain processing results with the following categories included:

- Year – year in which the video received Video of the year award
- Capacity – file size
- Duration – duration of the video
- Frame rate – number of frames per second
- Resolution – video resolution
- Number of frames – total number of frames contained in the video

- g) Changed pixels in whole video (absolute) – the number of pixel whose value has changed more that defined threshold expressed as a relative number
- h) Changed pixels in whole video (25 frames/sec) - the number of pixel whose value has changed more that defined threshold expressed as percentage, but the value has been weighted at 25 frames per second

YEAR	CAPACITY	DURATION	FRAME RATE	RESOLUTION	NUMBER OF FRAMES	NUMBER OF PIXELS	CHANGED PIXELS IN WHOLE VIDEO (ABSOLUTE)	CHANGED PIXELS IN WHOLE VIDEO (25 frames/sec)
1984	9.95 MB	3:02.978	29.960	352 x 162	5480	5655571560	0,070973804	5,92%
1985	12.8 MB	4:42.443	29.971	352 x 264	8463	12271007490	0,061188402	5,10%
1986	15.7 MB	4:59.960	25.000	480 x 360	7497	36665742885	0,110991331	11,10%
1987	22.7 MB	4:36.960	25.000	480 x 360	6922	48518218365	0,159070385	15,91%
1988	10.6 MB	2:39.640	25.000	480 x 360	3989	11427513390	0,065013535	6,50%
1989	14.9 MB	4:20.789	29.971	480 x 360	7814	32725852380	0,095045956	7,93%
1990	15.6 MB	5:14.880	25.000	480 x 360	7870	15212374350	0,043867042	4,39%
1991	18.7 MB	4:43.040	25.000	480 x 360	7074	46033061295	0,147679728	14,77%
1992	16.9 MB	4:18.283	29.917	640 x 360	7726	44133040740	0,097226912	8,12%
1993	24.3 MB	5:32.959	29.971	480 x 360	9977	63441149100	0,144306917	12,04%

Table 4 – Processing results for 1984 – 1993 videos

YEAR	CAPACITY	DURATION	FRAME RATE	RESOLUTION	NUMBER OF FRAMES	NUMBER OF PIXELS	CHANGED PIXELS IN WHOLE VIDEO (ABSOLUTE)	CHANGED PIXELS IN WHOLE VIDEO (25 frames/sec)
1994	17.2 MB	5:31.912	23.976	480 x 360	7726	44132342805	0,097225374	10,14%
1995	27.9 MB	5:14.441	29.971	640 x 360	9422	112791198630	0,203755555	17,00%
1996	21.3 MB	4:19.000	25.000	480 x 360	6473	35031062580	0,122818499	12,28%
1997	11.6 MB	3:56.565	29.971	640 x 360	7088	13544338515	0,03252456	2,71%
1998	25.5 MB	5:05.000	25.000	480 x 360	7623	108175713165	0,322047497	32,20%
1999	20.7 MB	3:56.398	29.971	640 x 360	7083	45487192230	0,109307317	9,12%

	MB			360				
2000	22.7 MB	4:27.335	24.000	480 x 360	6414	52408126320	0,18543246	19,32%
2001	22.6 MB	4:33.730	23.976	480 x 360	6561	47303294070	0,163620392	17,06%
2002	26.0 MB	4:59.213	23.976	480 x 360				0,00%
2003	23.8 MB	4:25.430	23.976	640 x 314	6362	78103998450	0,239568548	24,98%

Table 5 – Processing results for 1994 – 2003 videos

YEAR	CAPACITY	DURATION	FRAME RATE	RESOLUTION	NUMBER OF FRAMES	NUMBER OF PIXELS	CHANGED PIXELS IN WHOLE VIDEO (APPOSITE)	CHANGED PIXELS IN WHOLE VIDEO (25 frames/sec)
2004	23.6 MB	5:02.696	29.971	480 x 360	9070	68250509025	0,170771223	14,24%
2005	20.6 MB	4:47.618	23.976	480 x 360	6894	65903697105	0,216947466	22,62%
2006	13.3 MB	3:05.475	23.976	480 x 360	4445	42618898680	0,217593811	22,69%
2007	21.8 MB	4:12.959	23.976	640 x 360	6063	73297787775	0,20576933	21,46%
2008	17.4 MB	3:12.024	23.976	640 x 358	4602	92796166170	0,345128035	35,99%
2009	13.9 MB	3:18.695	29.971	640 x 360	5953	43746619350	0,125079449	10,43%
2010	21.5 MB	5:07.638	23.976	640 x 360	7374	65610760245	0,151443027	15,79%
2011	16.9 MB	3:53.648	23.976	640 x 360	5600	48232122390	0,146597205	15,29%
2012	19.0 MB	4:35.400	25.000	640 x 360	6883	60636419910	0,149945393	14,99%
2013	26.4 MB	8:20.329	23.976	640 x 360	11994	55406622105	0,078627592	8,20%

Table 6 – Processing results for 2004 - 2013 videos

Data in these tables are graphically presented in Figure 3. Unfortunately, the program kept reporting an error with 2002 video, the cause of which has not been successfully determined. Apart from columns representing percentages for each video, the graph also features a line representing linear approximation of expressed values, with appropriate linear function.

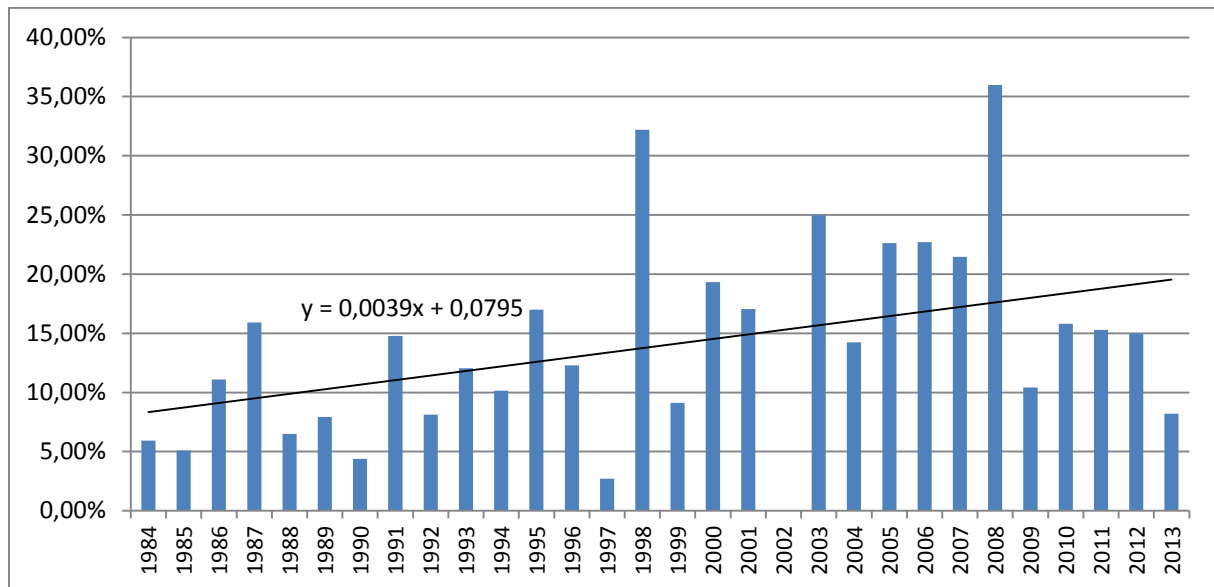


Figure 3: Graphic presentation of percentages of changes pixel weighted at 25 frames per second for all processed videos

6. CONCLUSION

Even a casual observer of reward-winning videos processed in this paper can see that something is happening with the production of said videos, since in the previous 30 years information density in them has been on a constant rise. The fact that we are not talking about subjective evaluation is shown by a function trend presented in Figure 3. This paper used relatively simple algorithm which measures information density and which features many shortcomings. But even that algorithm points to a trend observed in most video contents regardless of their distribution, i.e. an increase in information density. This trend should not be ignored since the content has previously been the focal point, but it is obvious that significant changes are occurring in the form for which we still do not completely understand what effect it has on viewers.

Further approach to this problem includes using more complex algorithms for movement detection, as well as correlation to methods used by other authors. In addition, it is necessary to investigate in detail how different compression algorithms affect analysis, as well as video content resolution. The final goal is to allow colleagues in the fields of humanities and social sciences to quantitatively express something they have so far only been able to describe qualitatively, i.e. the increase in information density in video contents and allow them to appropriately tackle that potential problem.

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