Color-based Recognition Techniques for Manipulation Detection in Advertisement Videos

Eric van Schaik
University of Twente
PO Box 217, 7500 AE Enschede
the Netherlands
e.j.g.vanschaik@student.utwente.nl

ABSTRACT
As marketing has become an increasingly advanced field of study, consumers are more successfully manipulated by advertisers, which robs them of part of their autonomy. This paper proposes techniques to automatically detect how manipulative an advertisement videos can be. Manipulation in advertisement videos can come in many different forms, and this paper focuses on the use of color. It combines insights drawn from existing literature into a design for new recognition techniques. This design is evaluated with a survey where the success of manipulation of advertisement videos is tested. This all results in a proof of concept for the automation of manipulation detection in advertisement videos.

Keywords
Manipulation, advertisement videos, detection, color

1. INTRODUCTION
The definition of marketing according to the Oxford Dictionaries is: “The action or business of promoting and selling products or services, including market research and advertising“. In many cases this is achieved through manipulation, i.e. to influence people’s choices “to the extent that it does not sufficiently engage or appeal to their capacity for reflection and deliberation” [10]. This definition of manipulation is laid out in extensive detail in a paper by Sunstein (2015), and is used here to ground the idea of manipulation as a detrimental advertising practice. Developments in the fields of psychology and behavioral sciences in the last decades has resulted in marketers being increasingly successful in manipulating the emotions of people on a subconscious level, and this can rob people of part of their autonomy [10]. In order to pave the way for organizations to give part of this autonomy back to consumers, this paper proposes techniques to automatically detect manipulation in video advertisements.

An obvious organization that would want to protect the autonomy of the consumer and defend certain moral values is the government, and for the Dutch government, there is already a committee that exists for this purpose, namely the Stichting Reclame Code (SRC). This committee handles any complaints that an advertisement violates the Dutch Advertising Code, and recommends and checks advertisers when it decides the Dutch Advertising Code is violated. It can be expected that two problems will arise with the rise of online advertisement videos, namely that there will be too many advertisements to handle, and that the advertisements come from international sources who are not bound by the Dutch Advertising Code. This paper addresses the first problem, proposing techniques that can automate part of the process, and the second problem can be solved by the (increased) collaboration with international organizations with the same goal. The SRC is already a member of the European Advertising Standards Alliance (EASA), and both are part of the International Council on Ad Self-Regulation (ICAS), so this is not a new problem for the SRC. These organizations are in part also candidates for the adoption of the techniques proposed in this paper.

Another type of stakeholder that can benefit from this are video services like YouTube, who are then able to present a new level of transparency regarding manipulation of advertisements, and thereby delivering a more comfortable user experience. This would be more realistic if the online video platform market would be more competitive [13]. It can also constrain the rising popularity of ad blocking software, by making consumers trust advertisements more and thereby benefiting the advertisers as well. Another way to bring this to market would have a third party develop the proposed techniques and either selling it or taking the open-source approach.

Before the design of manipulation detection techniques can be presented, a literature review of manipulation in videos is put forward, after which a design is proposed, developed and tested. The results lead to the proposal of an optimal design within the given framework.

2. MANIPULATION IN VIDEOS
A substantial amount of psychological and neuroscientific research has been done to determine the relation between videos and emotions. A study by Berger (2012) looked at the relation between emotions and the virality of videos, and found that videos that triggered high-arousal emotions like anger or awe had a higher chance of making a video viral than low-arousal emotions like sadness[1]. Teixeira (2012) also did a study looking at specific emotions and their relation to advertisement videos. They used facial expression detection to determine the level of joy and surprise, and they found that although there was a positive correlation between both emotions and the success of an advertisement, “the level rather than the velocity of surprise affects attention concentration most, whereas the velocity rather than the level of joy affects viewer retention most” [12]. In other words, to get a viewer to keep watching requires the joy of the video to come quick rather than that it is a lot of fun, whereas to get the viewer’s attention, it is better that the surprise of the video is bigger than that it comes quicker. Another study, by Lewinski (2014), also used facial recognition software to detect facial expressions of basic emotions, and found that there was a

30th Twente Student Conference on IT, Febr. 1st, 2019, Enschede, The Netherlands. Copyright 2018, University of Twente, Faculty of Electrical Engineering, Mathematics and Computer Science.

positive correlation between facial expressions of happiness during high- and medium-amusing video advertisements and attitude toward the advertisement and the brand, while finding no relation between other basic emotions and the effectiveness of advertisement [7].

Hereby the relation between (some) emotions, whether or not induced in a manipulative manner, and the success of an advertisement video is established. However, in order to automatically detect the level of manipulation in videos, the relation between emotions and (one or more of) the technical features of a video has to be determined. Therefore the rest of this literature review goes into the relation between some measurable technical features of a video (namely sound, length and color) and emotions.

2.1 Sound

Calderón (2018) conducted a study that looked at the congruence between audio and visual stimuli, and its relation to (the perception of) emotions [2]. They subjected viewers to videos with sound, where the sound of the videos was either congruent or incongruent with the content of the videos, and they looked at the heart rate of the viewers as an objective measure, and they asked for various dimensions of valence and arousal of each bimodal stimulus as a subjective measure. They found that the congruence of the audio and visual stimuli had an effect on the perception of emotions, but not on the actual heart rate.

A study by Song (2012) looked at the predictability of the visual gaze when comparing different uses of sound during a video [9]. They found that the visual gaze was most predictable when the sound fell into the category of human voices (speech, human noise and singers).

2.2 Length

Regarding the relation of the length of an advertisement video and the influence on the viewer, there is far less literature available. However a study by Krishnan (2013) showed that "a 15-second ad is 2.9% more likely to complete than a 20-second ad, which in turn is 3.9% more likely to complete than a 30-second ad" [6]. Oshiba (2002) on the other hand finds that the ideal advertisement length varies greatly per viewer, and proposes a system where streaming services tailors the length of an advertisement to the particular viewer [8].

2.3 Color

A study by Geslin (2016) looks into the relation between color properties in video games and the emotional response [4]. They found that there was a significant relation between saturation, lightness and illumination, and the emotions of joy, sadness and fear of the viewer/player. A related study by Kim (2015) proposes a computational method that could determine the theme color of an image, which would enhance the aesthetic and affective quality of the image [5]. Then as to which color is associated with which emotion, a study by Dael (2016) found that colors "along the red–yellow spectrum were deemed more appropriate for joy expressions and cyan–bluish hues for fear expressions" [3]. They also found that brighter and more saturated colors are associated more with feelings of joy than with feelings of fear.

Since it is not within the scope of this paper to cover all possible features, this research will focus primarily on the use of colors in videos, and its influence on the behavior of viewers. Color was chosen since the relation of color and emotion has the most support in the literature, and it is one of the more viable features of videos to develop automatic detection techniques for. In particular, the initial design will focus on the brightness, saturation and temperature of the videos.

Brightness is simply how light an image is. Saturation is a measurement to determine the how pure a color is. For instance, a RGB pixel where red is 255 while green and blue are 0, is considered to have a high saturation, while grey has a very low saturation. The more a certain color is combined with other colors, the less pure it becomes, and therefore less saturated. Temperature in this context indicates how 'warm' a color is, which can be described as red-yellowish. It is traditionally measured in kelvin, where color temperatures over 5000 K are considered cool, and color temperatures between 2700 K and 3000 K are considered warm. However, a coarser measurement of the temperature of an image will be used during this research.

3. RESEARCH QUESTION

Above problem leads to the following research question: "How would one best design techniques that detect various levels of manipulation in videos on the basis of color usage?" This question can be subdivided into several sub questions, namely:

- "What techniques already exist for extracting information on color usage in videos?"
- "Which of the existing techniques are useful for detecting various levels of manipulation?"
- "How would one best use these existing techniques to create new ways of detecting manipulation in advertisement videos?"

4. METHODOLOGY

4.1 Initial Design

In order to design techniques that can detect properties of videos, a concise overview of the existing image and video processing tools is needed. In particular, the boundaries of how much relevant information can be extracted from videos with the existing tools and how much would still need to be processed needs to be established. After planning the design of the techniques (which existing tools to use, which programming language to develop the techniques in), they are developed.

4.2 Evaluation

For testing a collection of advertisement videos is used, randomly selected from the Coloribus Advertising Archive by taking the 18 newest videos between 10 and 40 seconds. Then in order to establish the level of manipulation, two things need to be tested. First, the success of the advertisements is assessed. For this, a list of five crucial questions is used [11] as a foundation to structure an elaborate survey with a small number of participants. These five questions address how well the participants remember each advertisement, how likely they are to buy the product, how much they like each advertisement, if they can identify the key message of each advertisement, and how well the brand can be found online. Only the first four questions of this list are used for the interviews. The second thing that needs to be tested is how well the participants are aware of the influence of the color usage. As mentioned before, advertisements can be successful if they simply inform the viewer, but for the influence to be manipulative, it has to be in a way that the viewer is not aware of it. To measure this, participants are asked the reasons for the success of the best-scoring advertisements, so that it could be determined if they think it is related to the color usage.

Every participant is shown 6 advertisements in quick succession, after which they are asked to rank the advertisements in the order of how likely they are to buy the product, how much they like the advertisement, how well they can identify the key message of the advertisement, and what they think are the reasons for the success of the 3 advertisements they liked best. This is done three times, after which they are asked which brands they still remember.

To ensure that the specific grouping of the 18 videos into 3 groups of 6 does not have a significant impact on the results, 5 different test cases were used, where each case had a different, randomly chosen grouping.

5. RESULTS

5.1 Initial Design

5.1.1 Existing techniques

For this design to successfully combine the insights drawn from the literature with existing video processing techniques, the choice was made to use a programming language in combination with a video processing library. Unlike existing commercial video processing software like Adobe Premiere, this also provides the ability to expand freely on the ideas laid out in this paper with future research, which is the purpose of this paper.

Starting with the best programming language to use, three languages came up most often, namely C++, Python and Matlab. Consulting various blogs and forums, the following pros and cons could be distinguished.

Table 1. Assessment Programming Languages

	Pros	**Cons**
C++	Free, OpenCV written in C++, fast at video processing	Hard to learn and more complicated to quickly produce a prototype
Python	Free, lots of different available libraries, good OpenCV interface	Slower at video processing than C++
Matlab	Often used in academic fields and research, good at visualizing results	Commercial software, no programming experience, lot of overhead which can make video processing slow

All things considered, the choice for which programming language to use fell on Python. Being free and open-source, it would be well-suited for the expansion of the ideas described in this paper. Although being slightly slower with the OpenCV library than C++, it is easier to implement new ideas and experiment.

In choosing the right library to use for the manipulation detection, one library seemed to be by far the most popular, namely OpenCV. Taking Stack Overflow for instance, a question and answer forum for computer programmers, the tag 'computer-vision' was used in combination with the tag 'opencv' 3672 times, whereas it was used in combination with the tag 'tensorflow' 539 times, the second library in the list of most related tags. Same with the tag 'image-processing' the most related tag is 'open-cv' (7377 times). They estimate their number of downloads exceeding 14 million, with their library being used by Google, Yahoo, Microsoft and Intel [14]. Also being recommended by Medium and Packt Hub, and being free open-source software, OpenCV seemed the optimal choice [15][16].

5.1.2 Usage

The OpenCV library consists of a large amount of functions that are not necessary for the color-detection purposes, but the function that is used primarily is the transformation of color spaces of images. This part of the OpenCV library is used to retrieve the saturation level, the brightness level and the level of temperature of an image. Specifically, these values are calculated per pixel, where the saturation level produces a number between 0 and 255, the brightness level produces a number between 0 and 255, and the temperature level produces a number between -255 and 255 (the red values of RGB are calculated, ranging from 0 to 255, and then 0.5 times the green values and blue values are subtracted, which means that if $r = 0$, $g = 255$ and $b = 255$, this particular measurement of the temperature level would be -255). For an image, all these pixel values are summed up, divided by the number of pixels in the image, and rounded down. Then for a short advertisement video, this is done for every frame of the video, and divided by the amount of frames of the video.

5.2 Testing

5.2.1 Technical

For the unit testing of the Python code, a set of 10 random images has been picked, using an online random image generator [17]. These images are edited to increase or decrease the brightness, saturation and temperature. There are various tools to achieve this, and here the built-in functionality of Microsoft PowerPoint is used. Of each of these 10 images, 2 variations of each color property is made, resulting in 6 variations for each image. In other words, each image is edited with PowerPoint so that there is a brighter and less bright image, and same with saturation and temperature, resulting in 60 different images. Then using the manipulation detection tool, the brightness, saturation and temperature of the appropriate variations is determined. All the variations of every image are then checked to see whether the manipulation detection tool and the PowerPoint tool agree on which image scores higher on a certain color feature.

5.2.2 Evaluation

As mentioned in the methodology section, there have been randomly chosen 18 advertisement videos between 10-40 seconds, the manipulation scores of those videos have been calculated, and they are displayed below.

Table 2. Manipulation Scores

Brand	**Brightness**	**Saturation**	**Temperature**
Aldi	105	74	-2
Beefeater	231	84	16
Bonds	53	68	10
Booking.com	118	73	4
Corona	111	102	30
Geico	46	85	-14
KitKat	247	3	-2
McDonalds	123	56	13
Nike	91	44	0
Optrex	134	88	25
OtterBox	90	93	13
PIAF	230	17	7
Canary Islands	137	84	-12
Shiner Beer	147	66	17
Metropolitan Police	81	30	-2

Tommy John	116	72	10
Unimed Aracatuba	49	128	11
Walmart	138	94	-20

Given the scores above, the average brightness of the advertisement videos is 125, the average saturation is 70, and the average temperature is 6.

Then a survey was carried out with 11 participants, where the success of the advertisements was measured, along with the awareness of the color usage (also see methodology).

Table 3. Survey Scores 1

Brand	Likeability	Influence on buying behavior	Recognition of key message
Aldi	2.55	2.91	3
Beefeater	5.18	4.91	0
Bonds	2.64	2.09	3
Booking.com	2.91	2.82	1
Corona	2.64	2.09	3
Geico	4.55	5.09	0
KitKat	3.64	3.09	3
McDonalds	3.18	2.82	1
Nike	2.64	2.55	1
Optrex	3.91	3.91	1
OtterBox	2.73	2.82	1
PIAF	5.18	5.18	2
Canary Islands	2.55	2.91	2
Shiner Beer	2.91	2.45	1
Metropolitan Police	3.45	3.91	4
Tommy John	3.91	3.73	4
Unimed Aracatuba	4.27	4.45	2
Walmart	3.09	3.09	2

Table 4. Survey Scores 2

Brand	Memorability	Color-related reason for likeability
Aldi	3	0
Beefeater	2	0
Bonds	1	0
Booking.com	6	0
Corona	6	1
Geico	1	1
KitKat	6	0
McDonalds	6	0
Nike	7	1
Optrex	1	0
OtterBox	3	0
PIAF	2	0
Canary Islands	4	4
Shiner Beer	1	2
Metropolitan Police	4	0
Tommy John	1	0
Unimed Aracatuba	1	0
Walmart	5	1

Here the *likability* of an advertisement is the average position in a ranking of 6 random advertisements with the question "Which advertisements did you like best?", the influence *on buying behavior* is similar but with the question "Which product or service are you most likely to buy now that you have seen this video?", the *recognition of the key message* is the number of participants that could correctly identify the key message of an advertisement, the m*emorability* is the number of participants that could remember the brand of the advertisement at the end of the survey, and the *color-related reasons for likeability* is the number of participants that mentioned something related to color-usage when asked "What did you think were the best things about your top 3 advertisements of the [ranking of 6 most likeable advertisements]?".

Given the scores above, the average *recognition of key message* is 1.78, and the average *memorability* is 3.33, and the average ranking of the *likeability* and *influence on buying behavior* is naturally 3.5.

In both the tables the advertisements with above average *likeability* have been marked yellow.

6. CONCLUSION

Considering the brightness scores of the advertisement videos, there three outliers with scores above 200, none of which had an above average *likeability* score, suggesting that there is a threshold for the brightness above which the advertisement does not look appealing anymore. Also, there are three advertisement videos with brightness scores lower than 60, and none of these three videos had an above average *likeability* score either, suggesting that there is an optimal range of brightness for advertisements. Looking at the videos that are above average likeable, this range seems to be roughly between 90 and 130 (with the one video that scores below the threshold also being on the verge of the average *likeability*). The results with regards to saturation are more ambiguous however. Of the 10 videos with an above average *likeability*, only 6 had an above average saturation, and 3 out of the 4 most likeable videos had an above average saturation, giving only a slight correlation between a high saturation and success of an advertisement video. What can be said however is that only with exception of the Nike advertisement, all the advertisements that had a *likeability* of less than 3 had a saturation within the range of 65 and 105. In the case of the temperature, there even seems to be a small negative correlation, with only 4 of the 10 most likeable advertisements having a temperature above average.

As expected, there is a large correlation between the *likeability* of an advertisement and *the influence in buying behavior*, and also between those factors and the *memorability* of an advertisement, with 8 of the 10 videos with above average *likeability* having an above average *likeability*. However, there is no significant correlation between the *likeability* of an advertisement and the *recognition of the key message*.

Regarding manipulation, a small amount of participants indicated that color usage was a factor in their preference for certain advertisements, with only one advertisement where 4 participants indicated that color usage was a factor, and that advertisement video (Canary Islands) scoring high in both brightness and saturation.

This all results in an optimal design for color-based manipulation detection techniques within the framework laid out above, and according to the results of this survey. The initial design is used as starting point. It uses the OpenCV python library to extract the brightness, saturation and temperature, and gives an increase in each of them an equal increase in score.

First the various manipulation scores (*likeability, memorability, etc.)* are each given a weight and are summed up, so that the survey can produce a final score for each advertisement. The choice has been made to give the *likeability* a weight of 1, *influence on buying behavior* a weight of 0.2, *recognition of key message* a weight of -0.2, *memorability* a weight of -0.2 and *color-related reason for likeability* a weight of 0.5, so that the lower this score is, the higher the manipulation. Since the *likeability* and *influence on buying behavior* ranges from 1 to 6, and *recognition of key message, memorability* and *color-related reason for likeability* from 0 to 11 (due to the survey having 11 participants), this leads to a minimum score of 12.7 (lowest manipulation score) and a maximum of -3.2 (highest manipulation score). In this manner a measured manipulation score is given to each advertisement, and it would be expected for the optimal manipulation detection tool to have the biggest negative correlation between the measured manipulation and the sum of the brightness, saturation and temperature scores.

In the initial design the Pearson product-moment correlation coefficient (ranging from -1 to 1) between the brightness scores and the measured manipulation score is 0.235. This is most likely because of the few outliers that had a very high brightness score but turned out to score very low on the measured manipulation score. A straight-forward optimization would be to filter out the videos that have an average brightness between ±90 and ±130. This is tried, and using the range 90 to 130 to filter out everything that scores below or above that range (by setting the brightness scores of those videos to zero), it already improves the correlation coefficient to -0.543. To find the optimal range for the filtering, a program is written that first loops over all integers between 0 and 150 as lower bound and finds that the optimal lower bound is 52, and then loops over all integers between 0 and 300 as upper bound, finding that the optimal upper bound is 124. This range of 52 to 124 gives a correlation coefficient of -0.710. A similar strategy is implemented with regard to saturation, where the videos with a saturation score in the range of ±65 to ±105 would be used as initial range. With saturation the unfiltered correlation coefficient is 0.137, and using the intuitive 65 to 105 range, this is improved to 0.046. The optimal lower bound is found to be 88 when looping over all integers between 0 and 120, while the optimal upper bound is found to be 128 when looping over all integers between 94 and 200. This optimization gives a correlation coefficient of -0.342.

These optimizations can be combined into one manipulation detection score by taking the sum of the filtered brightness and saturation scores (0 if out of the optimal range) for each advertisement, which results in a correlation coefficient of -0.724. However, the brightness score has proven to be a better indication of the manipulation than the saturation, so when taking the sum of the brightness and saturation scores, it can be an improvement to only take a fraction of the saturation score while taking the whole brightness score. Again looping through a number of possibilities (0.001 to 1), the optimal fraction is found to be 0.496, resulting in a correlation coefficient of 0.746.

The temperature has proved not useful in this survey, and therefore more research is needed to use this aspect of advertisement videos for the detection of manipulation.

In conclusion, the optimal design for a manipulation detection tool that is found here takes the average brightness and saturation value per pixel in an advertisement, filters out the advertisements with brightness scores under 52 or above 124, and filters out the advertisements with saturation scores under 88 or above 128. Then it would take the remaining videos and add the brightness scores to a fraction of 0.496 of the saturation scores, and the resulting score would be an indication of the level of manipulation of an advertisement video.

7. DISCUSSION

The most challenging part of this research has been the evaluation of the design, and due to lack of time for more sophisticated methods, a small survey has been chosen. The results have been discussed above, and here some nuance is added. The advertisement videos were taken relatively randomly from an online archive, but some of the brands were significantly more known than others, which could have led to a less reliable memorability score. For instance, Booking.com, Corona, McDonalds and Nike all scored high on this success factor, while Optrex and Geico scored low. Also, it can be the case that the literature underlying this research (brighter and more saturated colors make an advertisement more successful) is so well known in the field of marketing that most of the chosen advertisements already score relatively high in these departments. This would mean that this research would be more useful to identify manipulative aspects in a random collection of videos than to use it solely on advertisements. Lastly, it can be expected that other elements of a short advertisement video play a large role in the success of the video. For example the sound and the content are also important factors of an advertisement video, and these factors are not taken into account here. Content in particular would have a large impact on the *influence on buying behavior* score, since not all participants are in the target group of every product. For instance, female participants would be far less likely to buy men’s underwear, and also for this reason the *likeability* score was given more priority in drawing conclusions from the results. This could be solved by having more participants and using more advertisements, but this research, being a proof of concept, is suitable for using as a starting point for further research.

8. ACKNOWLEDGMENTS

Thanks to Fons Wijnhoven for his guidance during the process of writing this paper.

9. REFERENCES

[1] J. Berger and K.L. Milkman. 2012. What makes online content viral? *J. Mark. Res.* 49, 2 (2012), 192–205. DOI:https://doi.org/10.1509/jmr.10.0353

[2] S. Calderón, R. Rincón, A. Araujo, and C. Gantiva. 2018. Effect of congruence between sound and video on heart rate and self-reported measures of emotion. *Eur. J. Psychol.* 14, 3 (2018), 621–631. DOI:https://doi.org/10.5964/ejop.v14i3.1593

[3] N. Dael, M.-N. Perseguers, C. Marchand, J.-P. Antonietti, and C. Mohr. 2016. Put on that colour, it fits

your emotion: Colour appropriateness as a function of expressed emotion. *Q. J. Exp. Psychol.* 69, 8 (2016), 1619–1630. DOI:https://doi.org/10.1080/17470218.2015.1090462

[4] E. Geslin, L. Jégou, and D. Beaudoin. 2016. How Color Properties Can Be Used to Elicit Emotions in Video Games. *Int. J. Comput. Games Technol.* 2016, (2016). DOI:https://doi.org/10.1155/2016/5182768

[5] E.J. Kim and H.-J. Suk. 2015. Hue extraction and tone match: Generating a theme color to enhance the emotional quality of an image. In *ACM SIGGRAPH 2015 Posters, SIGGRAPH 2015*. DOI:https://doi.org/10.1145/2787626.2787657

[6] S.S. Krishnan and R.K. Sitaraman. 2013. Understanding the effectiveness of video ads: A measurement study. In *Proceedings of the ACM SIGCOMM Internet Measurement Conference, IMC*, 149–162. DOI:https://doi.org/10.1145/2504730.2504748

[7] P. Lewinski, M.L. Fransen, and E.S.H. Tan. 2014. Predicting advertising effectiveness by facial expressions in response to amusing persuasive stimuli. *J. Neurosci. Psychol. Econ.* 7, 1 (2014), 1–14. DOI:https://doi.org/10.1037/npe0000012

[8] T. Oshiba, Y. Koike, M. Tabuchi, and T. Kamba. 2002. Personalized advertisement-duration control for streaming delivery. In *Proceedings of the ACM International Multimedia Conference and Exhibition*, 21–28.

[9] G. Song, D. Pellerin, and L. Granjon. 2012. How different kinds of sound in videos can influence gaze. In *International Workshop on Image Analysis for Multimedia Interactive Services*. DOI:https://doi.org/10.1109/WIAMIS.2012.6226776

[10] Cass Sunstein. 2015. Fifty shades of manipulation. (2015).

[11] Johanna Teichmann. 2017. Testing TV ads. *The Restless CMO*. Retrieved January 16, 2019 from http://therestlesscmo.com/post/testing-tv-ads

[12] T. Teixeira, M. Wedel, and R. Pieters. 2012. Emotion-induced engagement in Internet video advertisements. *J. Mark. Res.* 49, 2 (2012), 144–159. DOI:https://doi.org/10.1509/jmr.10.0207

[13] Online Video Platforms Market Share Report | Competitor Analysis | YouTube, Vimeo, Bits on the Run | Datanyze. Retrieved January 26, 2019 from https://www.datanyze.com/market-share/online-video

[14] About - OpenCV library. Retrieved January 27, 2019 from https://opencv.org/about.html

[15] Top 10 Computer Vision tools you must know - Packt Hub. Retrieved January 27, 2019 from https://hub.packtpub.com/top-10-computer-vision-tools/

[16] Tools to help you dive into Computer Vision – eSpace Technologies – Medium. Retrieved January 27, 2019 from https://medium.com/@eSpace/tools-to-help-you-dive-into-computer-vision-610181dd0df1

[17] Random Image Prompts. Retrieved January 19, 2019 from http://writingexercises.co.uk/random-image-generator.php