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Research paper

Gore Image Automatic Censorship Program

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Abstract

A Matlab-based automatic gore image censoring program is presented in this research. The program uses Alexnet to classify set of images as gore images and non-gore images. This pre-trained convolutional neural network is further trained to allow more dynamic applications that is able to successfully classify gory images. A gore image is an image that contains violent scenes such as bloods from human bodies and mutilated human bodies that may be disturbing to some audiences especially children. Four sets of images are used as such gore images, non-gore images, confusing non-gory images and a gore images with low threshold of blood. A total of 32773 images are tested. Results show that the modified Alexnet program can censor gore images and has an accuracy of at least 98.43% with a censoring rate of 20 seconds per image. Most of the errors in the classification process are due to low blood threshold and confusing non-gore images. This program can be used to improve the censorship capabilities of news media and other publication firms

Keywords: *Image Censoring, Gore, Neural Network, Alexnet*

1. Introduction

The broadcasting media has been an important aspect of our daily lives. Their services include news, announcements, entertainment, education and advertisement. However, there are times where certain images would make the audience feel uncomfortable due to their disturbing contents. In this regard, image censoring has been an important aspect in the media and other publishing organizations. One way to censor an image is by manual censoring where a person does the censoring of all the image. However, this process is prone to human errors and would consume time. Image processing and censoring can be used to accomplishe automatic classification and censorship of images. The main objective of this research is to automatically censor gore images. Gore images are defined as images which are gruesome and bloody. It can also be described as images showing an excessive amount of blood. This includes lacerations and dismemberment of body parts.

The fundamental tasks in the image censoring problem is the image recognition tasks. Several advanced researches are presented that provide a smooth and reliable method of image or facial recognition as presented by Cong Wang [1] in his paper. Gabor phase representation for distorted images is also presented in [2]. Neural network based facial recognition [3, 4] can also be used for low resolution images. This improves the recognition rate of programs intended for these kinds of applications. In another research [5], DFT can be used as a global descriptor for facial recognition. There may be hundreds of methodologies and algorithms that can be used for image and facial recognition but this research chose the convolutional neural network in Alexnet [6] to recognize and classify the images on test in the program. Once the image is classified as Gore image, the skin recognition becomes a vital task in the censoring process. Skin recognition and facial recognition is needed to pad the gore image with white segments. A good method of skin recognition is presented in [7].

2. Problem Statement

In current news, media outlets or any publishing firm, it is inevitable to come across images that contain violent graphics or gore images. Gore images are images that contain violent scenes containing blood or deformed or mutilated human bodies. These images maybe very distracting or controversial for certain audiences especially children. Nevertheless, it is somewhat important for some news correspondence to present such necessary content and evidence shown in some images. This research presents an automatic gore censoring program that allows a more efficient and fast method of censoring images. The program is based on the Alexnet Convolutional Neural Network which is trained for censorship tasks. This censoring program aims to automatically detect and censor gore images. Only parts of the image that are considered gore will be censored. Once the image is classified as a gore image, the face of the person in the image will also be automatically censored. This program is helpful in media and publishing firms as they no longer need extra labor for manual censor editing.

3. Methodology

Alexnet convolutional neural network is known for its ability in image classification with high accuracy rates. The Alexnet program will be trained further to detect gore images in an image file. These gore images will then be censored by the program by replacing the gore images with white images. The overall function of the Gore censor program is shown in figure 1.

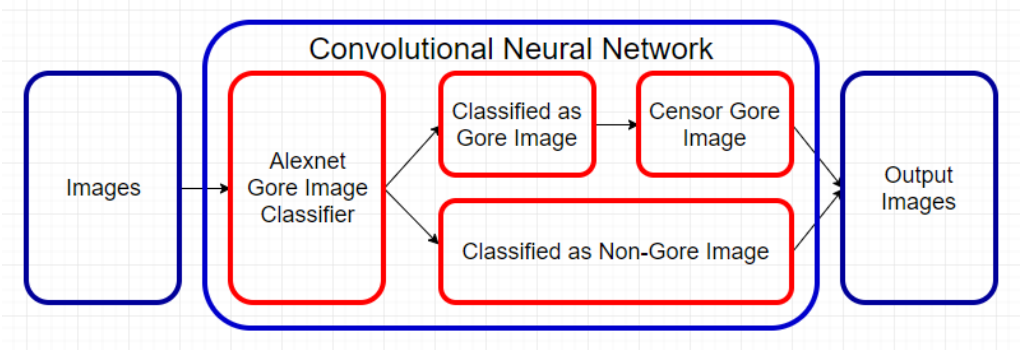

Fig. 1 Overall Function of the Gore Censor Program

Figure 1 shows the functionality of the gore image censor program. This program is implemented using Matlab. Images are analyzed by the Alexnet convolutional neural network and each image will then be classified as either a gore image or a non-gore image. All images that are classified as non-gore images will go directly to the output, while those images classified as gore images are further processed by the program to recognize images such as human face, human skin and human body. The program also recognizes the presence of blood in the image. If a human face is detected in a gore image, that human face will also be censored for the purpose of privacy. Other gore or violent images are likewise censored by the program. This allows the output images to be non-distracting to the viewers.

The program is limited to filter gory images alone. Gore images could be a mutilated body with or without the presence of blood. However, since the term gore is too general, the program limits the censorship to pictures from crime scenes and movie scenes with a horror/violence theme, pictures with color red in it and pictures with hidden body parts like when you close your fist, your hand would appear like the fingers are missing. The dataset used in this research is shown in figure 2.

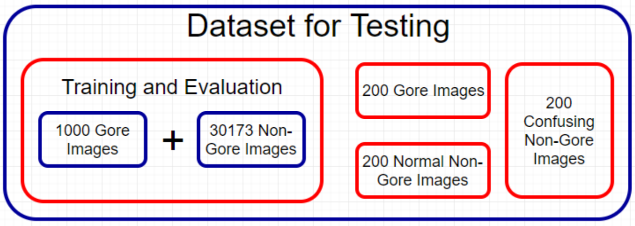

Fig. 2 Dataset Used in Gore Censor Program

Figure 2 shows the dataset used in this research. The Alexnet convolutional neural network was trained using 1000 gore images and 30173 non gore images. A total of 31173 images are used for the training and evaluation of Alexnet. During the testing and implementation stage, 600 images are added to the previous set of images. From the 600 images, there are 200 gore images, 200 normal non-gore images and 200 confusing non-gore images. Confusing non-gore images are those images that contain red colors for the shirts or any other item that may be recognized as blood by the classifier. The images used as dataset were obtained through Google images [8], Caltech101 [9], INRIA, Beyond Frontal Faces: Improving Person Recognition Using Multiple Cues for non-gore images while the gore images came from Google images and best gore.

More images were included in the dataset to build a more accurate gore sensor. A huge percentage of images added were dedicated to people wearing red so that the network to be able to recognize the differences between the shades of red in blood and of red hues in cloths. Images for humans with painted skin were also added to the dataset. Multiple images of tribe members, that have a tradition of painting their skin were also used. Images from festivals, especially the Indian color festival, were also used. The goal was for the gore detector to improve its recognition accuracy between colors. Table 1 shows the summary of the dataset used in this research

Table 1': Summary of Dataset

Image Type	Image count
Gore (included in the training set)	1000
Gore (additional test images)	200
Non-gore (included in the training set)	30173
Confusing Non-gore (additional test images)	200
Normal Non-gore (additional test images)	200

The confusing non-gore images are those images with plenty of red colors in them. These red color marks may confuse the network and may lead to a false recognition of blood leading to false gore classification. 200 confusing non-gore images are used to train the Alexnet to increase its ability to distinguish the difference between blood and red items on the image. Figure 3 shows examples of confusing non-gore images.

Fig. 3 Samples of Confusing Non-gore Images

Figure 3 shows several samples of confusing non-gore images. These are images containing red hues such as red clothes, lipsticks and other shades of red. The Alexnet is trained to recognize these images as non-gore.

4. Discussion of Results

The Alexnet underwent several additional training sequences to make it suitable in classifying gore and non-gore images. These training sequences were done according to the correct classification of the images. The Alexnet training and evaluate routine resulted in a coefficient of correlation of 0.998. A Matlab graphical user interface was designed to simplify the test for the gore censor program. Figure 4 shows how the gore-censor program is able to classify the confusing non-gore image correctly.

Fig. 4 Classifying Confusing Non-Gore Image Correctly

Figure 4 shows correct classification done by the gore censor program. The network correctly identified the red clothes and no censorship is done on the image.

Once gore the image is classified as gore, the network identifies the part of the image which are human faces, blood and other parts of the body that are mutilated. These parts of the image are padded with white as a way to censor the image. Figure 5 shows one example of the outcome of censoring a gore image using the proposed program.

Fig. 5 Censoring a Gore Image from Alexnet

Figure 5 shows how the program censors a gore image. Once an image is classified as gore, the human face, blood and skin textures are padded with white color. The ability of the program to correctly cover the disturbing images with white is not yet perfect. Figure 6 shows an example of censoring a gore image. Due to the lighting that caused a different shade of the red color for blood, the program is not able to entire replace the disturbing image by white. However, the result shows that the censored image is not as disturbing as the original image. This is one of the delimitations of the proposed network.

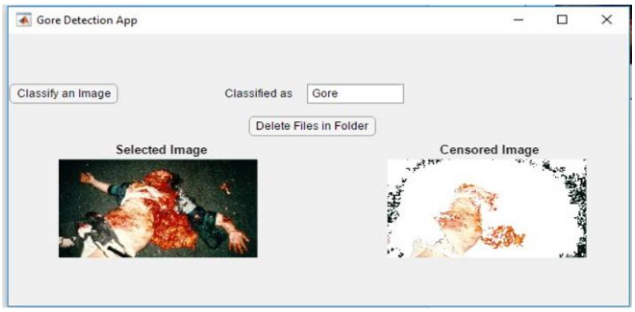

Fig. 6 Censoring a Gore Image with Different Lighting Effects

Another delimitation of the gore censor program is the threshold on the amount of blood in the image. If there is too little blood in the image particularly in the parts of the skin, the network confusingly recognizes the image as non-gore. Figure 7 below an example wherein the person in the picture contains too little red shades for blood. The network confusingly classified the image as non-gore and it is not able to censor the image.

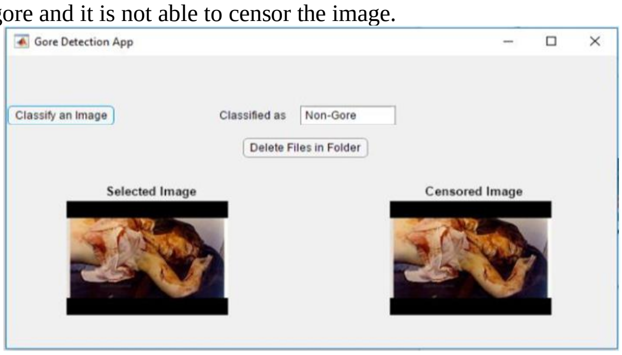

Fig. 7 Censoring Gore Image with Low Threshold of Blood

The gore censor network program was tested initially to demonstrate the ability of the Alexnet to classify a gore image and a non-gore image. Table 2 below shows a summary of the initial test done using the proposed network. Images from training dataset are those images that are used during the training and evaluation of the network. The additional data set are those images used for testing but not included in the images during the training and evaluation.

The overall test was done using all the available images classified by Alexnet. Table 3 shows the summary of the results gathered from classifying a total of 31, 773 images. 31, 173 images are used in the training and evaluation of the Alexnet.

Additionally, the overall performance of the network is shown in table 4 below.

Table 2: Initial Test Results

Test	Category	Source and number of images		Classified as gore	Classified as non-gore	accuracy	Percent accuracy
		Training dataset	Additional data set				
1	Non-gore	20	0	0	20	20/20	100%
2	Non-gore	0	20	0	20	20/20	100%
3	Gore	20	0	20	0	20/20	100%
4	Gore	0	29	27	2	27/29	93.10%
5	Confusing Non-Gore	0	20	0	20	20/20	100%

Table 3: Overall Test Results

Test	Category	Source and number of images		Classified as gore	Classified as non-gore	accuracy	Percent accuracy
		Training dataset	Additional data set				
1	Gore	1000	0	996	4	996/1000	99.6%
2	Non-Gore	30173	0	433	29740	29740/30173	98.56%
3	Gore	0	200	191	9	191/200	95.5%
4	Confusing Non-Gore	0	200	42	158	158/200	79%
5	Normal Non- Gore	0	200	12	188	188/200	94%

Table 4: Result for Correct Classification

Type of Classification	Result	%Accuracy
Gore classified as gore	1,187/1,200	98.92%
Non-gore classified as non-gore	30,086/30,573	98.41%
Total correct classification	31,273/31,773	98.43%

It is also noteworthy to know the nature of errors in the network. Table 5 shows a summary of errors committed by the network in the process of classifying gore and non-gore images.

Table 5: Result for Incorrect Classification

Type of Classification	Result	%Error
Gore classified as Non-gore	13/1,200	1.08%
Non-gore classified as Gore	487/30,573	1.59%
Total Incorrect classification	500/31,773	1.57%

Table 5 shows the summary of errors in classifying gore images. Most of the errors in the classification are due to the confusing non-gore images. The Alexnet needs to be trained further to improve the classification of the non-gore images.

5. Conclusion

The Alexnet was trained further to classify images as gore images or no-gore images. Gore images are limited to the images containing bloods and mutilated human bodies that may be distracting to young audiences. A Matlab based program uses the Alexnet to censors the parts of the image classified as gore. Censoring is done by replacing the distracting parts of the image by white paddings. Tests show that the network can successfully classify a gore image and a non-gore image and has an accuracy rate of 98.43%. However, errors in the classification is found due to the confusing non-gore images. Furthermore, the threshold of the blood content in the classification process is quite high. For this reason, gore images that contain small volume of blood are classified wrongly as non-gore images. Additional training and more images are required to improve the performance of the proposed gore-censor program.

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