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Illicit Image Detection: An MRF Model based Stochastic Approach

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Abstract:- The steady growth of the Internet, sophisticated digital image processing technology, the cheap availability of storage devices and surfer's ever-increasing interest on images have been contributing to make the Internet an unprecedented large image library. As a result, The Internet quickly became the principal medium for the distribution of pornographic content favouring pornography to become a drug of the millennium. With the arrival of GPRS mobile telephone technology, and with the large scale arrival of the 3G networks, along with the cheap availability of latest mobile sets and a variety of forms of wireless connections, the internet has already gone to mobile, driving us toward a new degree of complexity. In this paper, we propose a stochastic model based novel approach to investigate and implement a pornography detection technique towards a framework for automated detection of pornography based on contextual constraints that are representatives of actual pornographic activity. Compared to the results published in recent works, our proposed approach yields the highest accuracy in detection.

I. INTRODUCTION

Accessing the Internet with the computers and a range of other communicating devices are increasingly a modern day must have for children and young people around the globe. Not only are they establishing new cultural norms, they are also becoming mainstream within education. A great majority of minors globally spend bulk amount of their time online to locate their educational stuff and as a source of perfectly innocent fun and games. But every child and young people who uses the Internet will almost certainly be exposed at some stage to material that will shock and possibly harm them, or they will come into contact with organization or individuals who mean them injury. To follow potentially catastrophic consequences throughout a children's lifetime, he/she needs only one such encounter to go wrong. It is therefore, no surprise that the Internet as well as the social networking sites pose a serious threat to our children who are more or less vulnerable, either some or all of the time while they are on the Internet. The risks posed by criminals who attempt to share, exchange, consume and produce child exploitation material,

however, are fairly clear, and law enforcement is faced with the difficult task of trying to deal with the sheer volume of material (and offences) in a streamlined and systematic way.

Research [1] shows some of the statistics on pornography as shown in the pie-chart below;

Fig. 1: Worldwide Pornographic Revenue (Courtesy: TopTen Reviews)

Apart from the exposure of age inappropriate content to minors, dealing with pornography in the workplace is a serious challenge for many large organizations but employing a block-all-images Internet browsing and email policy no longer provides a viable solution. In a paper written by McGuire et al. found that the viewing of pornography can serve as a source of a paraphilic "vivid sexual fantasy" which, when contemplated during masturbation, may condition men into perversion [2]. Further, research also established a direct link between pornography consumption and crimes like sexual abuse, rape, violence, and child molestation [3], [4], [5].

* Every second - \$3,075.64 is being spent on pornography
* Every second - 28,258 internet users are viewing pornography
* Every second - 372 internet users are typing adult search terms into search engines

Table 1: Pornography Statistics: TopTen Reviews

Research showed that most of the audience belongs to the lower levels that gradually progress towards higher levels. If we are able to put a stopping mechanism somewhere in this low level area, it will protect people from entering the most exiting world of arousal and being pornography addicted.

Fig. 2. Progression Model for Pornography Consumer

Contemporary research established a link between child pornography and adult pornography. From that point of view, it will not only prevent people from viewing the most erotic and bestial images but also put an end for the potential paedophiles who are currently belongs to less severe groups to progress further towards most severe groups that eventually make them professional paedophiles at some stage. From the studied literatures, we find a progression model for pornography consumer as shown in Fig. 1.

So, there is a fundamental demand in real time classification of images to block inappropriate contents at home and in a business or commercial environment. The problem therefore is the detection and prevention of certain types of images. Real-time detection of pornography can effectively prevent pornographic images from entering at home and into the workplace via email and Internet browsing.

The software industry suggests two types of solutions to combat with the problem of pornography - collecting the adult web site addresses and collecting key words of adult web pages. While the former allows the user to access the requested page upon verifying its IP address, the latter performs the content analysis for providing access to the user. Here, the filtering programs block the pages from viewing upon finding any related key word of the web page in user's computer. The drawback of these systems is that it is an uphill task to collect all adult web site addresses because hundreds of new web sites are launching every day. The drawback of the latter system is that it tends to block the sex education pages due to the key words used on these pages. In addition, pornographic websites introducing new keywords to attract peoples and minors, that are being most often used by the users during browsing.

We are interested in the computational foundations of vision that helps us designing machine vision systems with applications to pornographic image detection. Our proposed project aims to find out the solutions for some fundamental

questions in computer vision. How can we recognize persons, guns, cars, boats and many other suspicious categories of objects in cluttered pictures? How can we be trained these categories in the first place? Can we provide machines with ability akin to this?

The remainder of this paper proceeds as follows: In Section II we present previous work in this specific field. In Section III, we describe our proposed pornography detection model, which estimates body part appearance models for pictorial structures using latent relationships between the appearances of different body parts. Experimental results demonstrating the accuracy and efficiency of the proposed approach are discussed in Section IV and finally in Section V, we present our conclusion and future work.

II. RELATED WORK

While significant research have already been conducted on pornography or illicit image detection most often with miscellaneous low and high level features, and other visual cues in fact, no research has looked closely at the subject.

In fact, all the pornography detection approaches are based on skin detection module that defines a decision rule based on which skin and non-skin pixels will be discriminated. A decision rule based on the distance of the pixel color to skin tone using a metric plays the crucial role in the discrimination process as this metric is defined by the skin color modelling technique. The final goal of skin-color detection is to choose a classifier that will discriminate between a skin and a non-skin. From classification point of view, skin-color detection can be viewed as a two class problem: skin pixel vs. .non-skin pixel. Literature suggests different classifiers are employed by different authors for skin detection based on their respective contexts, where data distributions or data modelling played a crucial role. Our literature review suggests three specific types of skin modelling techniques - Explicitly defined skin region, Non-parametric distribution modelling, Parametric distribution modelling, and Adaptive modelling. In Explicitly Defined Skin Region techniques, threshold is a parameter that stipulates the values a pixel can be if it is to be considered as skin. In Nonparametric distribution modelling, Normalized Lookup Table (LUT), Naïve Bayes Classifier, and Self Organizing Map (SOM) are most often used as skin classifier. Single Gaussian, Mixture of Gaussians, Multiple Gaussian Clusters, and Elliptical Boundary Model are mostly used as Parametric Model for skin color detection. Adaptive skin model employs two or more skin-color models from the models as discussed above in combination or in sequence to make the technique robust against the varying conditions. In other word, it is called 'Hybrid Model'.

Most of the adult image or pornographic detectors employed these skin color models based on different color space along with some other high level features like shape, color moment, color mean, region descriptors for their classification schemes.

A mathematical approach of grouping the images using the detected skin regions and extracted high level region features

from these regions that might have link to the pornography is called pornographic classification, which is mainly focussed on classification of the skin region into benign or pornographic. We can broadly categorize pornographic image classifier into three groups: Supervised Machine Learning, Geometric Classifier, and Boosting Classifier. Supervised Machine Learning can be further categorized hereunder into four groups. Supervised Machine Learning can be further categorized hereunder into four groups - Support Vector Machine [6], [7], [8], Neural Network, Decision Tree [9], and K-Nearest Neighbour [10]. Fleck et al. demonstrated an affine-invariant model that define human as a set of rules describing how to assemble possible girdles and spine-thigh groups, where both the individual geometry of the body parts and the relationships between parts are constrained by the geometry of the skeleton which eventually provides an appropriate and effective model for human body recognition [11]. Bootstrapping induces a classifier on a small set of labelled data and a large set of unlabeled data. Lee et al. reported an increase of sensitivity from 81.74% to 86.29% with boosting algorithm [12].

Cusano et al. reported better performance of SVM than multiple decision trees [6]. Bosson et al. found that neural networks (83.9specificity) gave slightly better results to that of k-NN and SVM [13]. Bosson et al. attained 94.7% sensitivity and 95.1% specificity using NN with MPEG-7 Descriptors. Zheng et al. [11] found that DT is able to provide better accuracy than NN and SVM [13]. Xu et al. demonstrated superior performance of k-NN over NN [10].

Almost all the existing techniques proposed region descriptors that are in fact, not directly aimed at capturing contextual constraints representatives of pornography rather based on some heuristic high level statistical and geometrical features on skin region like area, size, shape, location, and their relationships in terms of some ratios, resulting poor performance in finding the actual pornographic stuff on images and thus failing to utilize its full potential in areas like detection of pornography. Further, the extracted features as employed in the existing work are found to be vulnerable under the inherent imaging artifact like intensity inhomogeneity, scale, rotation, transformation, occlusion, and camera viewpoint. These are the void in the literature that this research is attempting to fill.

III. OUR PROPOSED APPROACH

Although the identification and detection of pornographic activity in an image is easy to a human observer, automatic and accurate identification is difficult and complex. Obtaining satisfactory detection results depends mainly on the ability of the descriptors in characterizing pornographic contextual constraints.

Segmentation of skin colour often used as feature in different face and human tracking applications plays a crucial role in locating and identifying a naked human object in an image. Initially, skin regions of an image are segmented based on the colour to reduce the search space, resulting a faster

approach appropriate for real time applications. Literature suggests a significant contribution in skin detection area over the last decade. Different authors suggested different approaches for skin detection based on different colour model out of which YC_rC_b playing a dominant role due to the fact that the luminance and chrominance components in this colour space are stored separately [14], [15], [16], [17], [18], [19], [20]. As a result, YC_rC_b is greatly suited to skin detection and some authors[14] reported found that the YCbCr gives the best skin detection results compared to seven other colour space transformations. In fact, we are not going to contribute anything in skin detection rather we use an existing skin detection technique [17] that has been found to be robust.

The resulting segmented skin region of a body is then divided into two parts – upper body part and lower body part that are independently searched with our proposed approach to detect pornography specific contextual constraint. While the upper body part is searched for detecting breast, the lower part is for pubic areas, especially the genitalia.

We employ Markov Random Fields (MRF) model to encode the contextual constraints representative of pornography and use these constraints as prior knowledge on pornographic activity in an image during classification. Markov Random Fields (MRF) model theory is found to be extremely robust in capturing contextual contexts in an image, especially under noisy condition.

A. Feature Extraction and Selection

Feature extraction and selection are the keys to robust and accurate image classification and in fact, play the most crucial role in pornography detection in this particular work. Here, we proposed a new hybrid feature derived from the generic low level features like colour and texture, which has been found to be robust and accurate in characterizing the appearance and internal structure of an image region.

- **Color Feature:** 50 skin patches are collected by just cropped off the segmented body region in each training image. A new low level color feature is derived utilizing the pure chromatic information (u and v) of the original CIE-Luv color model as;

$$Chroma_{(u,v)} = C_{(u,v)} - C_{(u,v)} - mean \quad (1)$$

Where, $N =$ Nos. of pixels in a single skin patch, and

$$C_{(u,v)} - mean = \frac{\sum_{n=1}^N C_{(u,v)}}{N}$$

Dropping the luminance component 'L' and considering 'u' and 'v' values, offering us a significant advantage for utilising pure color information in the detection process. Using pure color information, a skin model or detector gets an

ability to be able to adapt to the changes in the lighting and the viewing environment. The key advantage of being a lighting invariant color spaces made few spaces like *CIE-Luv*, *YCbCr*, and *HSI* the most popular choices to the research community working on skin detection.

In addition to the color, texture is another feature that can be employed as a cue for image analysis. Texture features are constructed in such a way that they characterize local variation in intensity or color within the neighbourhood surrounding the pixel. As a result, a value is assigned to the pixels with a given texture. Research suggests, color and texture based analysis are in combination capable of producing more accurate results than either the color or texture feature used independently [24].

Literature suggests the wavelet transform outperforms its other counterparts while applied in cluttered image having complex background. The wavelet transform has the capability to capture subtle texture information on objects appear on cluttered background more precisely than other texture descriptors [24]. Based on wavelet transform we derive a more powerful texture descriptor that is found to be robust in discriminating even subtle differences in texture.

- **Texture Feature:**

In a similar manner like *chroma* feature above, we define another low level texture feature employing the diagonal, horizontal, and vertical coefficients as yielded by the DWT as;

$$dwt_{(d,h,v)} = coef_{(d,h,v)} - coef_{(d,h,v)} - mean \quad (2)$$

Where, $N = \text{Nos. of pixels in a single skin patch, and}$

$$coef_{(d,h,v)} - mean = \frac{\sum_{n=1}^N coef_{(d,h,v)}}{N},$$

where $coef_{(d,h,v)}$ denotes diagonal, horizontal, and vertical coefficients.

However, mixing weight of colour and texture, which is pertinent to accuracy in capturing image appearance throws an open problem. Up to date research, computer vision and image processing in particular do not provide any authenticat-

Fig. 3. Mixing weight of colour and texture

ed relationship between these two while applied in combination, which incite us to run an experiment to find out an optimal weight ratios of these two. In our experiment, we have sourced 100 pornographic images freely available on the Internet and run an MLE (Maximum Likelihood Estimation) based segmentation scheme on these images to segment skin regions on them. Misclassification rate are plotted against both colour and texture component to find a cogent mixing weight.

Percentage of colour and texture components are taken at 5% interval starting from 10% to 90% and the graph is plotted on the mean classification error based on the segmentation results as obtained for the 100 images as chosen earlier. The plotted curve shows its minimum at 65% colour and 35% texture. So, we use this mixing weight of colour and texture in our work.

In addition to the colour and texture low level features, we add another powerful local image region descriptor called the 'Local binary patterns' (LBP). The LBP has been found to be a powerful feature allowing a classifier or detector to exploit fundamental properties of local image texture efficiently and effectively in a classification or matching. Applying LBP on an image yields occurrence histogram, which is a powerful texture descriptor that contains information about the distribution of the local micro-patterns like edges, spots, flat areas, over the image region. Label for every pixel of the image is assigned by the original LBP operator applying a thresholding technique on the centre pixel with his 3x3 neighbourhood.

- **Local Binary Feature:** Local Binary Patterns were originally introduced as a texture descriptor by Ojala [21], and have subsequently been employed as face and expression identification features [22], [23].

$$LBP_{P,R}(x_c) = \sum_{p=0}^{P-1} u(x_p - x_c) 2^p \quad u(y) = \begin{cases} 1, & y \geq 0 \\ 0, & y < 0 \end{cases} \quad (3)$$

where p = nos. of neighboring pixels, R = radius of the neighborhood.

In this particular work, local binary patterns are extracted from the individual chromatic channels to preserve channel-wise discriminative ability in terms of LBP.

Now, we combine these extracted low level features to get a high dimensional feature vector representative of each individual image and image object, which we call Luminance Invariant Region Descriptor (LIRD) ;

$$LIRD = \left[\sum_{n=1}^N \{ (chroma_{(u,v)}) * 0.65 + \{ dwt_{(d,h,v)} \} * 0.35 + lbp_{(r,b)} \} \right] \quad (4)$$

B. Classification

For pixel classification, we employ the MAP-MRF labelling, where $P(f | d)$ is the posterior distribution of an MRF. In Bayes labelling, it's an important step to derive this distribution. The problem here is to labelling the pixel into

two class – malign (pornographic) or benign (normal). So, it's a binary classification problem. Assuming the joint prior distribution of a pornographic image is

$$P(f) = \frac{1}{Z} e^{-U(f)} \quad (5)$$

$$\text{where } U(f) = \sum_{ij} \sum_{i' \in \{i-1, i+1, j-1, j+1\}} (f_{ij} - f_{i'j'})^2$$

is the *prior energy* for an image contains pornographic contents. Assuming that the observation is the true pornographic object on images plus independent Gaussian noise, $d_{ij} = f_{ij} - e_{ij}$, where $e_{ij} = N(\mu, \sigma^2)$, then the likelihood distribution will take the form

$$p(d | f) = \frac{1}{\prod_{i=1}^m \prod_{j=1}^n \sqrt{2\pi\sigma^2}} e^{-U(d|f)} \quad (6)$$

Where $U(d | f) = \sum_{i=1}^m \sum_{j=1}^n (f_{ij} - d_{ij})^2 / 2\sigma^2$ is the *likelihood energy*. Now, we can compute the posterior probability as

$$P(f | d) \propto e^{-U(f|d)} \quad (7)$$

Where

$$\begin{aligned} U(f | d) &= U(d | f) + U(f) \\ &= \sum_{i=1}^m \sum_{j=1}^n (f_{ij} - d_{ij})^2 / 2\sigma_{ij}^2 + \sum_{i=1}^m \sum_{j=1}^n (f_{ij} - f_{(i-1, j-1)})^2 \end{aligned} \quad (8)$$

is the *posterior energy*. The MAP estimate is equivalently found by minimizing the posterior energy function

$$f^* = \arg_f \min U(f | d) \quad (9)$$

The only parameter that we need to estimate is σ_{ij} , which can be done by employing the EM (Expectation and Maximization) algorithm. Now, $U(f | d)$ is fully specified and the MAP-MRF solution is completely defined.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

We have sourced the pornographic images freely available on the Internet for training and testing purpose. Selected images are full body frontal and of upright position with a 10 to 15% tilt in horizontal direction. All the images are divided into upper body part and lower body part. Upper body parts and lower body parts are now projected separately to a common coordinate frame, where they are roughly aligned in location and scale. We apply our novel descriptor LIRD on both the parts taken from the 200 images for feature extraction that

eventually are employed for training our classifier to classify pornographic object and pornographic image in terms of *likelihood energy* and *prior energy* respectively. The *likelihood energy* and *prior energy* for non-pornographic object and benign (normal) image are considered as rest of the world i.e., $\neg U(d | f)$ and $\neg U(f)$ respectively.

For testing purpose, we have downloaded another 200 images – 100 full body frontal pornographic images in upright position with a 10 to 15% tilt in horizontal direction, and 100 normal human body images that do not contain any pornographic activity and have similar orientation. All the images are divided into two parts akin to the training images as done earlier. Skin segmentation is done on pornographic test images to detect the naked skin followed by division of the same into two parts – upper body parts and lower body parts cutting halfway through the belly button. We employ a person detector [25] to locate the person in the normal images to reduce the search space followed by the same procedure to get the upper body and lower body parts.

Pixel labelling is done on upper body parts and lower body parts separately for detection of breast and genitalia respectively using the MAP-MRF labelling as derived earlier in the previous section.

An experimental study reveals that pornography detection rate increases with increase of the number of pixel labelled to pornographic in an image up to a certain point. We have obtained such an optimal point i.e., 60%, which yields maximum detection accuracy. Above 60%, no significant improvement has been noticed in our experiments. Details of the experiments are not provided here due to space constraint.

A popular measure, called Precision and Recall (Eq. 10), based on True Positive (TP), True Negative, False Positive (FP), and False Negative (FN) is applied on both - our experimental results and the results obtained from another pornography image detector proposed by Belem & Cavalcanti [24] to evaluate the performance of our novel approach. We selected Belem & Cavalcanti [24] for performance comparison as its authors reported more than 90% accuracy. Apart from the Precision and Recall, we also compared accuracy (Eq. 11) of our approach with Belem & Cavalcanti [8].

$$\text{Precision} = \frac{TP}{TP + FP} \quad (10)$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Accuracy} = \frac{TP + TN}{P + N} \quad (11)$$

Method	TP	FP	FN	TN	PRE	REC	Acc
Bel. & Cav. [24]]	161	61	39	139	0.73	0.81	0.75

Proposed	189	32	19	168	0.86	0.95	0.89
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Upper Body Parts

Method	TP	FP	FN	TN	PRE	REC	Acc
Bel. & Cav. [24]]	161	61	39	139	0.73	0.81	0.75
Proposed	189	32	19	168	0.86	0.95	0.89

Lower Body Parts

Table 2: Comparison of performance between the proposed and Bel. & Cav. [24] approach for lower body parts

We experienced a bit lower performances with Bel. & Cav. [24] than what claimed by the authors. The low performance might be attributed to the use of unconstraint images in this particular work.

V. FUTURE WORK AND CONCLUSION

We have proposed a novel pornography detection approach, where pornography specific contextual contexts based on few low level image features are encoded to detect pornography with maximum accuracy. The proposed approach is primarily aimed at detection of pornography specific objects in an image using MRF model, which has been found extremely effective while dealing with unconstraint and cluttered images. The proposed approach is applicable to the frontal images with upright position but can be extended by modelling other pornographic orientations (non-frontal and non-upright) as well. To the best of our knowledge, this is the first of its kind which is able to recognize pornography using actual pornography specific contextual constraint and thus paves the way for research in this area to not only help pornography detection, but also to contribute significantly in security & surveillance, human body movement and pose identification, medical imaging and much more.

REFERENCES

- [1] J. Ropelato, "Internet Pornography Statistics", Retrieved March 2009, from <http://internet-filter-review.toptenreviews.com/internet-pornography-statistics.html>.
- [2] R. J. McGuire, J.M. Carlisle, and B.G. Young "Sexual deviations as conditioned behaviour: A hypothesis". *Behaviour Research and Therapy* 2: 185-90, 1964.
- [3] M. H. Silbert, and A. M. Pines, 1984, "Pornography and sexual abuse of women". *Sex Roles* 10: 857-68, 1984.
- [4] D. L. Carter, R. A. Prentky, R. A. Knight, P. L. Vanderveer, and R. J. Boucher, "Use of Pornography in the Criminal and Developmental Histories of Sexual Offenders". *Journal of Interpersonal Violence* 2: 196-211, 1987.
- [5] E. M. Alexy, W. B. Ann, and A. P. Robert "Pornography Use as a Risk Marker for an Aggressive Pattern of Behavior Among Sexually Reactive Children and Adolescents". *Journal of the American Psychiatric Nurses Association* 14 (6): 442-453, 2009.
- [6] Ruiz-del-Solar1, V. Castañeda, R. Verschae, R. Baeza-Yates, and F. Ortiz, "Characterizing Objectionable Image Content (Pornography and Nude Images) of Speci_cWeb Segments: Chile as a Case Study", in *Proceedings of the Third Latin American Web Congress (LA-WEB'05, IEEE)*.
- [7] C. Jeong, J. Kim, and K. Hong, "Appearance-Based Nude Image Detection", in *Proceedings of the 17th International Conference on Pattern Recognition (ICPR'04)*, IEEE Computer Society, Washington, DC, USA, 2004.
- [8] Q.F. Zheng, W. Zeng, , W.Q.A. Wang, and W.Gao, "Shape-based Adult Image Detection", in *International Journal of Image and Graphics (IJIG)*, vol. 6(1), January 2006, pp. 115-124.
- [9] D. Chai and A. Bouzerdoum, "A Bayesian approach to skin color classification in YCbCr color space", in *IEEE TENCON'00*, vol. 2, pp. 421-424, 2000.
- [10] Y. Xu, B. Li, X. Xue, and H. Lu, "Region-based pornographic ImageDetection" in IEEE 7th Workshop on Multimedia Signal Processing, 2005.
- [11] M. Fleck, A. Forsyth, and C. Bregler, "Finding Naked People", in *Computer Vision - ECCV'96, 4th European Conference on Computer Vision*, Cambridge, UK, Volume II, pp. 593-602, 1996.
- [12] J.-S. Lee, Y.-M. Kuo, P.-C. Chung, and E.-L. Chen, "Naked image detection based on adaptive and extensible skin colour model", in *Pattern Recognition*, vol. 40(8), pp. 2261-2270, August 2007.
- [13] Y. Wang, W. Wang, and W. Gao1", Research On the Discrimination of Pornographic and Bikini Images", in *Proceedings of the 7th IEEE International Symposium on Multimedia (ISM'05)*, 2005.
- [14] M. Storrang, H.J. Anderson, and E. Granum, "Skin Colour Detection under Changing Lighting Conditions", 7th Symposium on Intelligent Robotics System, 1999, Coimbra, Portugal.
- [15] D. Chai, and K.N. Ngan, "Locating facial region of a head-and-shoulders color image", in *ICFGR'98*
- [16] K.W.Wong, K.M. Lam, and W.C. Siu, "A robust scheme for live detection of human faces in color images", in *Signal Processing and Image Communication*, vol. 18(2), pp. 103-114, 2003.
- [17] Q. Zheng, M. Zhang, and W. Wang, "A Hybrid Approach to Detect Adult Web Images", in *Advances in Multimedia Information Processing- PCM 2004, 5th Pacific Rim Conference on Multimedia*, Tokyo, Japan, Proceedings, Part II PCM (2), pp. 609-616, November 30 - December 3, 2004.
- [18] R. Khan, J. Stöttinger, and M. Kampel, "An Adaptive Multiple Model Approach for fast Content-Based Skin Detection in On-Line Videos", in *Proceeding of the 1st ACM workshop on Analysis and retrieval of Events /actions and workflows in video streams - AREA'08* , pp. 89-96, 2008.
- [19] Q. Ye, W. Gao, W. Zeng, T. Zhang, W. Wang, and Y. Liu, "Objectionable Image Recognition System in Compression Domain", in *Intelligent Data Engineering and Automated Learning, 4th International Conference-IDEAL 2003*, Hong Kong, China, pp. 1131-1135, Springer-Verlag publication, 2003.
- [20] L. Cao, X. Li, N. Yu, and Z. Liu, "Naked People Retrieval Based on Adaboost Learning", in *International Conference on Machine Learning and Cybernetics, IEEE '2004*, ISBN: 0-7803-7508-4, Beijing, vol.2, pp. 1133 - 1138, 2004.
- [21] T. Ojala, M. Pietikainen, and D. Harwood, "A Comparative Study of Texture Measures with Classification Based on Feature Distributions", *Pattern Recognition*, vol. 29, pp. 51-59, 1996.
- [22] T. Ahonen, A. Hadid, & M. Pietikainen, "Face recognition with local binary patterns". In *8th European conference on computer vision*, 2004, pp. 469-481.
- [23] C. Shan, S. Gong, & P. McOwan, "Conditional mutualinformation based boosting for facial expression recognition", in *Proceedings of the British machine vision conference*, 2005.
- [24] R.J.S. Belem and J.M.B. Cavalcanti "SNIF: A Simple Nude Image Finder", *Proceedings of the Third Latin American Web Congress (LA-WEB'05)*, IEEE, 2005.
- [25] V. Ferrari, M. Marin-Jimenez, and A. Zisserman. Progressive search space reduction for human pose estimation. In *CVPR*, Jun 2008.