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Evaluating Input Graphical Parameters for the Training Phase of Designing an Intelligent Emotional Vector Deducing Engine

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***Abstract*— Designing an intelligent engine to predict the emotion vector from graphical parameters of unfamiliar photograph stands the main research objective and this paper addresses graphical input evaluation problem for the training phase of the proposed engine. The emotion vector values are considered three dimensional and classified according their vector values to obtain trainable groups are subjects for the training phase. The results suggest the contribution of color and the 4 added parameters, sums of edges, corners, regional maximums and regional minimums of affective photographs increase the training accuracy. This paper further addresses the affects of above 4 parameters.**

***Keywords*— International Affective Picture System, Emotion Vector, Intelligent Engine, Artificial Neural Network**

I. INTRODUCTION

In resent psychological studies it is known that a human emotion can be represent by a set of three dimensional vectors defines as Valence (pleasant vs. unpleasant), Arousal (calm vs. exited) and Dominance (dominance vs. control), denotes V, A and D bellow. Therefore in affective researches all three VAD vectors should be addressed simultaneously.

So when it comes to design affective computer systems and relevant interfaces, and psychological applications it would be a fair approach to design an intelligent emotional vector deducing engine (IEVDE) from graphical data of the emotional photographs, that would provide us the capability to predict the emotional vector within a certain range of accuracy from an unfamiliar picture, as well as would be capable of omitting the strenuous data analytical processes that start from questionnaires to emotional vector obtain. Especially this type of engine could be usable for emotional image retrieval when combine with an affective wearable which could address the vectors to acceptable accuracy range.

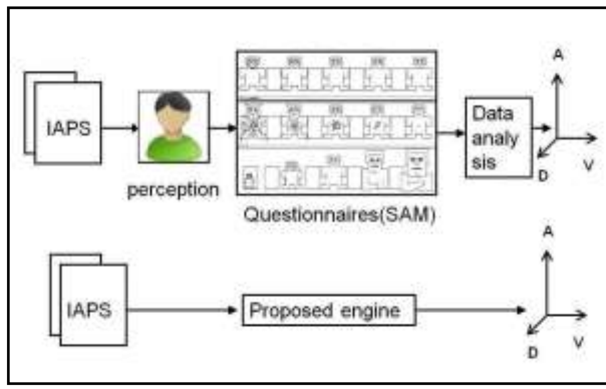

Fig. 1 intelligent emotional vector deducing engine

Using emotional vector value which could improve the design perspective such as proposed method comes as an object layer that consist of a simple three numbers which could be implemented into an application which would run even on a low spec platform against conventional methods that require mass storage and data mining techniques etc.

The accuracy of applying human emotions in applications is low due to the complexity issues, but is a growing field which combines computer science, arts and psychology. Existing publications are mainly about affective image classification and relevant parameter obtaining. In [10] V.Yanulevskaya et al. used valence vector to group IAPS into 10 discrete groups and tested the classifier using wiccest and gabor features of image textures. In [11] Jana Machajdik et al. combined colors, textures, compositions and contents which cover features from photography and existing researches to achieve better performance.

In existing researches, restrictions and limitations such as neglecting the affect of a particular vector such as dominance or only a limited number of selected photos instead of full photoset are applied to minimize complications, increase accuracy and to guarantee the sustainability of the trained model. In our approach we used full photo set and all three vectors without applying restrictions to evaluate low level graphical parameters in their original states and their potential through direct training and questionnaire based assessment. Also testing using the gray scale makes it a different approach. i.e. Black and white photographs are also very emotional.

In this research we consider that the parameters suited for the training phase and the clustering (classification) phase are different from each other, such as the former could to be better performed with more color information where the latter is somewhat simple and consist of less color information due to possible similar color occurrences between groups and be better addressed with graphical features like edges, corners etc.

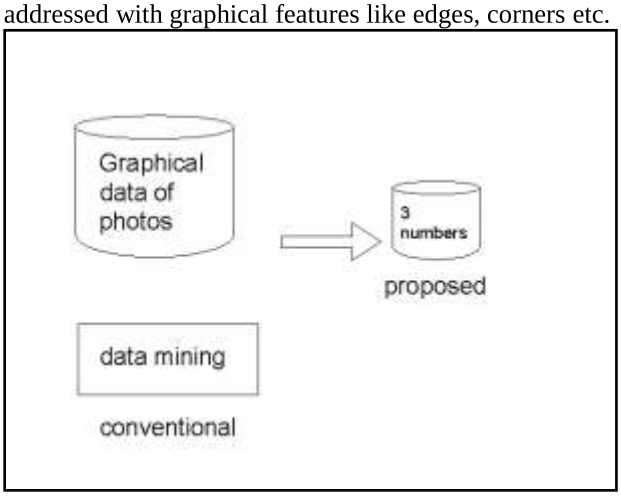

Fig. 2 Prospects of intelligent emotion vector deducing engine

II. DESIGN OF THE PROPOSED ENGINE

The proposed method to design intelligent emotional vector deducing engine is through training the artificial neural network using two consecutive steps that consist of clustering phase and training phase, by using graphical parameters of 1182 photos (set for all subjects) from the International Affective Photo System (IAPS) as inputs, and the known emotional vectors scaled from 0 to 9 as targets, mentioned in IAPS.tech manual.1-20-2008 (reference [1]). The data set for all subjects is used in this research, assuming that it provides us with a wider range of emotional vectors. The following figures indicate VAD plots of the set for all subjects

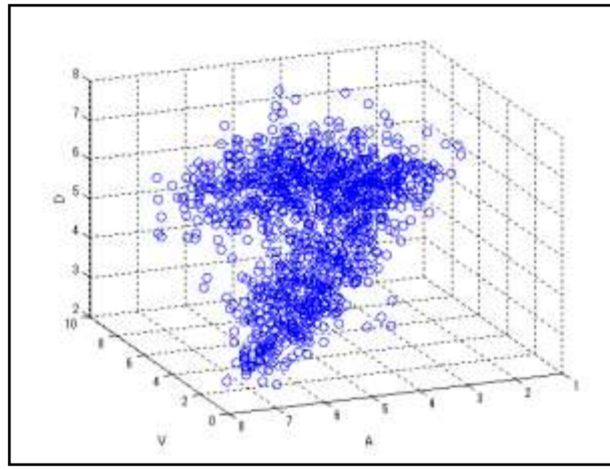

Fig. 3 emotional vectors VAD (3D plot)

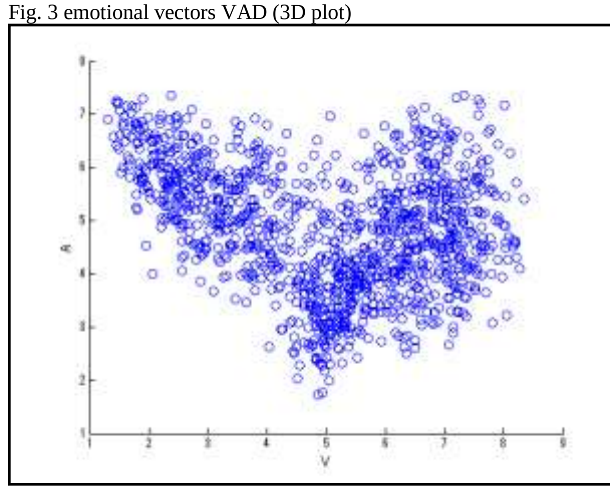

Fig. 4 emotional vectors (2D plot of V and A)

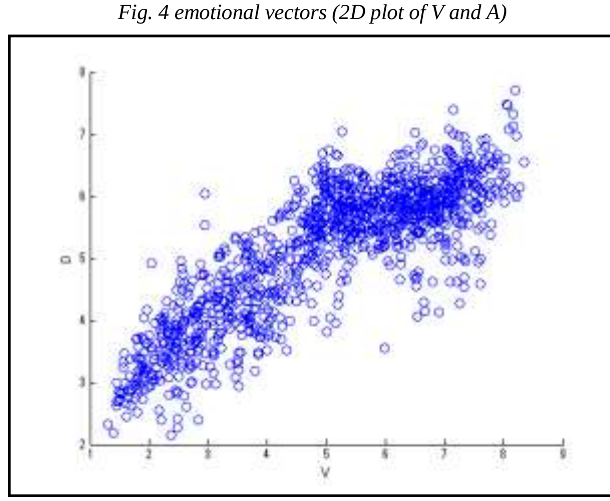

Fig. 5 emotional vectors (2D plot of V and D)

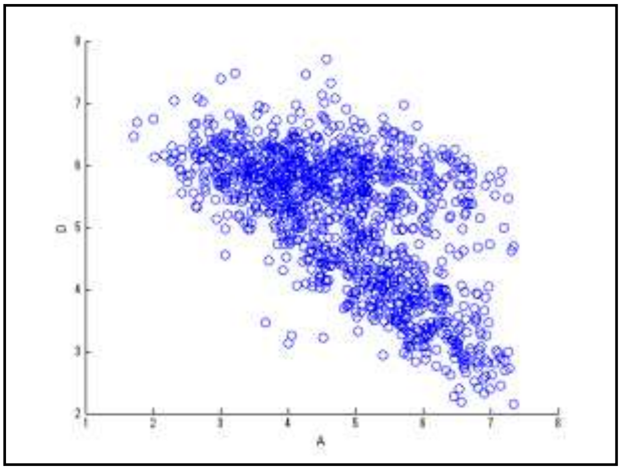

Fig. 6 emotional vectors (2D plot of A and D)

The design process depends on technical capacity of artificial neural network fitting tools and graphical features of affective photographs. The fitting tools that used have a limited capacity. Also vector range is taken into consideration. This design is considered in two phases, the clustering phase (classification) and the training phase.

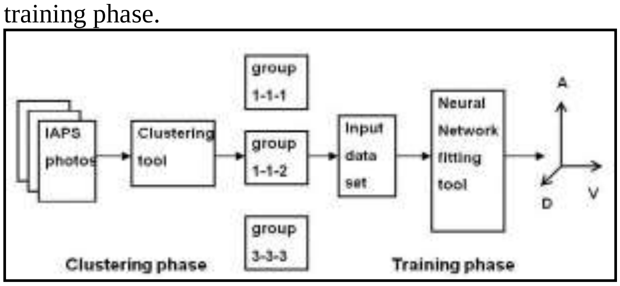

Fig. 7 designing of intelligent emotional vector deducing engine

Considering the macroscopic nature of this research, the research objective is to obtain and organize information from small number of graphical inputs which are more practical in place of content based complex information, also alternate to more complicated models that use skin conductance or brain waves to increase accuracy.

III. Obtaining Trainable Data Groups

The first approach was about the trainability issue and the relevant input parameters. This was achieved within the groups that formed by using pre known emotional vectors VAD (denotes output groups) from the IAPS set for all subjects.These groups were proven to be trainable in previous effort in reference [6] and at that time the suited input graphical parameters were proven to be consist of minimums and maximums of RGB histograms and 4parameters such as sums of edges, corners, regional maximums and regional minimums (denotes 4parameters). In this paper, the RGB histograms and the gray scale histograms are re-sectored to yield better training accuracy.

The output groups were formed in this paper and in reference [6] in such a way that the pre known emotional vectors V,A,D from the IAPS (the set for all subjects) are subject to clusterization using self organizing map(SOM) of artificial neural network. The relevant algorithm that used is batch unsupervised weight/bias training, which is capable of splitting the data into clusters according to their location of the space.

In training phase, output groups are organized as a 3 primary groups, then re-cluster each group into 3 sub groups that results in 9 groups. Training within these 9 groups is proven to be possible but both low in precision and efficiency, due to limited technical capacity of neural net fitting tools. Therefore a further clusterization into 3 groups is took place, which brought the total number of groups into 27, and within these groups training was proven to be considerably efficient and accurate.

IV. Input Data Scales

The data sets used for both phases are based on the histogram data, matrix specified parameters such as regional maximum and regional minimum and graphical parameters like no of edges and corners. Since the histogram data is directly influenced by the size of each photo, all photographs are of same size. The experiment results of reference [6] proved that the suitable input data set was 10parameter scale. Also proved that full usage of RGB scale (used the full color histogram) and the gray scale was less accurate due to presence of too much parameter, therefore during this effort each histogram is split into 8 sectors and sum the values within each sector is considered. As input data sets the following are considered.

(1).Use the 8 sectored gray scale histogram. (denotes as graysec8 scale bellow)

(2).adding the 4 parameters scale(sum of edges, sum of corners, sum of regional matrix and sum of regional minimum) to graysec8 scale(denotes as gray4 scale bellow)

(3).adding the 4 parameter scale to 8sectored color histograms (denotes rgb4scale bellow)

(4).adding the 4 parameter scale to minimums and maximums of RGB (denotes as 10 parameter scale which is similar to that of in reference [6])

Consideration of these scales as input data are based on social believes and assumptions which are to be assessed through experiments.

(1) Contribution of color toward emotion.

(2) Gray scaled photos are more emotional and timeless.

(3) Contribution of color red to photos shows mutilation.

(4) Photos with high arousal vector and the other vectors dormant shows higher numbers of edges.

In addition to the above the following parameters are considered to improve the training accuracy.

(5) The number of corners

(6) Matrix specified parameters such as regional maximums and regional minimums

V. INPUT EVALUATION

The training algorithms used are,

Lavenberg-Marquardt back propagation (trainlm)
Scaled conjugate gradient (trainscg)
Resilient back propagation (trainrp)
One step secant back propagation (trainoss)

Numbers of hidden layers are set 30 for all training sets for a unified evaluation schema. The testing method is such that use the data sets of all photos and their known vector values(V,A,D) except that of the test sample as inputs and targets to train neural network with different existing algorithms, then use the test sample's input as a test input to the trained network. Compare the predicted vector values from the network (denotes V_{test}, A_{test}, D_{test}) with the known VAD value of the test sample. If the predicted value is close enough to that of the test sample, the input data set is considered to be an appropriate set.

The groups that subject for training test are as follows

Group 1-1-1
V=6.64 to 8.05 A=3.08 to 4.30 D=5.20 to 7.49
Description:
Polar bears, dog, horse, giraffes, butterfly, rabbit, antelope, Elephants, mother, boys reading, neut baby, children, girl, Family, binoculars, chef, children, couple, balloons, fields, romance, flowers, nature, garden, clouds, sky, mountains, Courtyards, lake, ice cream, carnival ride

Group 1-2-1
V=5.79 to 7.23 A=4.26 to 5.51 D=5.33 to 6.37
Description:
shark, lizard, pony, gorilla, woman, cheer leaders, man in pool, gym, diving, clowns, pregnant, attractive men and women, dancing, smiling girl, gold, erotic males and females, couples, weight lifter, beach boys, romance, wedding, harbor, mountain, flowers, pastry, ice cream, alcohol, fast food, ferry, street, cards, thrilling sports, mascot

Group 2-2-1
V=5.93 to 7.14 A=2.51 to 3.43 D=5.72 to 7.40
Description:
Parrots, gannet, butterfly, grouper, adult, neut children, men and women, flowers, field, grain, nature, ocean, violin

Group 2-2-3
V=5.19 to 6.07 A=3.31 to 4.66 D=5.16 to 6.40
Description:
frog, shrimp, octopus, attractive men and women, erotic men and women, makeup, farmer, butcher, boy, men and women mother, artist, couples, medical worker, feet, bed, musicians, quilting, man with dog, propeller, bakers, beer, urinating, male dancer, condom, Venus fly trap, cockpit, mushrooms, cave, desert, whistle, food, abstract art, vase, barbells, puzzle, luggage, headlight, car, clock, light bulb, building, store, card dealer, stairs, chess, crochet, bridge, rowing, race cars, runner

Group 3-1-1
V=1.52 to 2.45 A=5.78 to 6.91 D=2.77 to 3.95
Description:
Bloody kiss, sad children, native boy, open grave, accident, Fire, mutilation, injury, dead body, battered female, stitches, Execution, severed hand, plane crash, assault, attack, gang, Starving child, soldiers, injured dog, vomit, sliced hand, dead man, man on fire, dog, KKK rally, car accident

Group 3-3-1
V=3.35 to 5.16 A=5.31 to 6.97 D=3.51 to 4.98
Description:
Snakes, spiders, attack dogs, leopard, bear, tiger, baby, scream, surgery, open chest, sick baby, incubator, volcano, lava, aimed gun, attack, police, aircraft, sky scraper, rock climber, oil, fire, biking/train, biker on fire, matador

VI. EXPERIMENT RESULTS ON TRAINING PHASE

The following results show the predicted vector values that clear the each marginal values of the relevant group (denotes margin clearance). If all three predicted vector values are within the minimum and maximum of the group, the sample is considered as passed

$V_{min}<V_{test}<V_{max}$
$A_{min}<A_{test}<A_{max}$
$D_{min}<D_{test}<D_{max}$

TABLE I
GROUP 1-1-1 MARGIN CLEARANCE RATES

Test scale	No of tests	Passed	Passed ratio
rgb4	225	154	68.4%
gray4	225	144	64.0%
graysec8	225	133	59.1%
10parameter	225	126	56.0%

TABLE 2
GROUP 1-2-1 MARGIN CLEARANCE RATES

Test scale	No of tests	Passed	Passed ratio
rgb4	375	249	66.4%
gray4	375	232	61.9%
graysec8	375	192	51.2%
10parameter	375	204	54.4%

TABLE 3
GROUP 2-2-1 MARGIN CLEARANCE RATES

Test scale	No of tests	Passed	Passed ratio
rgb4	100	63	63.0%
gray4	100	59	59.0%
graysec8	100	45	45.0%

10parameter	100	49	49.0%

TABLE 4
GROUP 2-2-3 MARGIN CLEARANCE RATES

Test scale	No of tests	Passed	Passed ratio
rgb4	360	248	68.9%
gray4	360	234	65.0%
graysec8	360	207	57.5%
10parameter	360	161	44.7%

TABLE 5
GROUP 3-1-1 MARGIN CLEARANCE RATES

Test scale	No of tests	Passed	Passed ratio
rgb4	175	120	68.6%
gray4	175	94	53.7%
graysec8	175	86	49.1%
10parameter	175	88	50.3%

TABLE 6
GROUP 3-3-1 MARGIN CLEARANCE RATES

Test scale	No of tests	Passed	Passed ratio
rgb4	220	142	64.6%
gray4	220	121	55.0%
graysec8	220	105	47.7%
10parameter	220	116	52.7%

The difference between predicted vector values and pre known vector values denotes as prediction difference dif_V, dif_A and dif_D bellow and the average difference value denotes dif_{ave} which could be used for evaluation.

$dif_V=|V-V_{test}|$
$dif_A=|A-A_{test}|$
$dif_D=|D-D_{test}|$
$dif_{ave}=(dif_V+dif_A+dif_D) / 3$

TABLE 7
AVERAGE DISTANCE VALUES OF EMOTIONAL VECTORS FOR TEST GROUPS

	Test Group					
scale	1-1-1	1-2-1	2-2-1	2-2-3	3-1-1	3-3-1
rgb4	0.43	0.41	0.39	0.36	0.38	0.47
gray4	0.52	0.48	0.46	0.41	0.44	0.56
graysec8	0.80	0.71	0.53	0.56	0.68	0.71
10parameter	0.74	0.63	0.51	0.73	0.65	0.67

With the evaluation parameters margin clearance rates and average difference values of emotional vectors above, the following can be considered as achievements.

(1): accuracy increase is observed by adding 4 parameters to a particular histogram based data scales.

(2): both rgb4scale and gray4 scales are accurate than 10 parameter scale.

(3): The gray4 scale is also competitively accurate against the rgb4scale.

(4): color increases the training accuracy

VII. AFFECT OF 4 PARAMETERS

During the input parameter evaluation, the above 4 parameters that consist the sum of edges, corners, regional maximums and regional minimums improved the training accuracy.

In this section the affect of them are tested for average of each vector valued three selected photographs that represent each group by adjusting the graphical effects as follows. The groups subject to this test are same as that of the training test.

Since the addition of external objects to the content of photographs possibly alter the affects, are avoided during this test and the following are considered to be appropriate adjustments.

(1) Sharpen the image (increase of edges)
(2) Adding noise to the image (increase of corners)
(3) Increase of minimum
(4) Decrease of maximum

Although these parameters do not act independently from each other, the adjustments 1, 2 above increase edges and corners with least change of histogram.

Adjustments 3,4 that change the minimums and maximum not only changes the brightness and colors of photographs, but also histogram. Therefore to avoid interferences by color changes, mono chromed photographs are used for minimum and maximum adjustments.

The experiment method was using self assessment manikins (questionnaires) immediately after one minute of perception time. Estimation ranges are set from 1.0 to 9.0 with allowed one digit below zero for evaluation accuracy.

The following test results indicate the difference of emotional vectors after adjustments, i.e. affect of 4 parameters.

TABLE 8
SUBJECTS: 20 MALES, AGE BETWEEN 40 TO 60

group	sharpening			adding noise			increase minimum			decrease maximum		
	V	A	D	V	A	D	V	A	D	V	A	D
1-1-1	-0.61	0.19	0.38	-0.14	0.06	-0.07	-1.11	0.92	-0.65	1.14	-0.81	1.14
1-2-1	-0.71	0.23	0.51	-0.04	0.03	-0.08	-1.12	0.71	-0.81	1.11	-1.10	0.96
2-2-1	-0.57	0.16	0.87	0.06	0.04	-0.17	-0.62	0.81	-0.53	0.51	-0.49	0.72
2-2-3	0.11	0.23	0.86	0.00	-0.07	-0.17	-0.65	0.82	-0.57	0.55	-0.51	0.61
3-1-1	-0.81	1.03	-1.01	0.11	-0.81	-0.10	-0.71	1.14	-0.63	0.81	-0.95	0.43
3-3-1	-0.53	1.08	-0.79	0.17	-0.63	0.06	-0.61	1.13	-0.62	0.64	-1.01	0.52

TABLE 9
SUBJECTS: 20 FEMALES, AGE BETWEEN 40 TO 60

group	sharpening			adding noise			increase minimum			decrease maximum		
	V	A	D	V	A	D	V	A	D	V	A	D
1-1-1	-0.72	0.34	0.41	-0.16	0.04	-0.07	-1.21	0.92	-0.69	1.78	-0.92	1.22
1-2-1	-0.66	0.41	0.54	-0.08	0.07	-0.08	-1.20	0.81	-0.77	1.74	-1.11	1.23
2-2-1	-0.09	0.21	0.88	0.07	0.03	0.16	-0.71	0.68	-0.44	0.61	-0.71	0.73
2-2-3	-0.11	0.33	0.84	0.06	-0.06	0.14	-0.67	0.73	-0.54	0.60	-0.52	0.71
3-1-1	-1.06	1.23	-1.02	0.17	-0.82	0.08	-0.82	1.19	-0.64	0.81	-1.14	0.52
3-3-1	-0.86	1.15	-0.98	0.18	-0.74	0.09	-0.66	1.16	-0.57	0.71	-1.16	0.51

TABLE 10
SUBJECTS: 40 MALES, AGE BETWEEN 20 TO 25

group	sharpening			adding noise			increase minimum			decrease maximum		
	V	A	D	V	A	D	V	A	D	V	A	D
1-1-1	-0.48	0.27	0.44	-0.17	-0.06	0.14	-0.89	0.79	-0.68	1.04	-0.81	1.16
1-2-1	-0.28	0.21	0.48	-0.08	-0.05	-0.09	-0.91	0.62	-0.78	0.87	-1.14	0.98
2-2-1	-0.36	0.17	0.53	-0.11	-0.07	-0.18	-0.71	0.73	-0.24	0.45	-0.51	0.73
2-2-3	0.31	0.37	0.73	0.06	-0.08	-0.24	-0.76	0.71	-0.43	0.53	-0.51	0.62
3-1-1	-0.65	1.19	-0.86	0.15	-0.79	0.06	-0.54	0.79	-0.71	0.52	-0.74	0.62
3-3-1	-0.56	1.18	-0.77	0.18	-0.76	0.08	-0.66	0.91	-0.61	0.61	-0.78	0.72

TABLE 11
SUBJECTS: 40 FEMALES, AGE BETWEEN 20 TO 25

group	sharpening			adding noise			increase minimum			decrease maximum		
	V	A	D	V	A	D	V	A	D	V	A	D
1-1-1	-0.67	0.31	0.38	-0.12	0.06	-0.08	-1.27	0.88	-0.62	1.72	-0.77	1.12
1-2-1	-0.61	0.32	0.26	-0.06	0.07	-0.09	-1.21	0.72	-0.79	1.63	-1.15	1.13
2-2-1	0.13	0.24	0.56	0.08	0.05	-0.16	-0.81	0.79	-0.53	0.66	-0.72	0.71
2-2-3	0.16	0.37	0.78	0.06	-0.08	-0.16	-0.73	0.71	-0.63	0.68	-0.61	0.58
3-1-1	-0.95	1.01	-0.88	0.12	-0.88	0.06	-0.89	1.19	-0.72	0.77	-1.12	0.54
3-3-1	-0.87	1.18	-0.71	0.18	-0.82	0.04	-0.71	1.23	-0.61	0.78	-1.10	0.38

The following are the achievements of affect test results.

1. Sharpen the image (increase of edges)

Reduces of V in group 1-1-1 and group 1-2-1, makes a photo less pleasant.

Increase of D in group2-21 and group 2-2-3, suggests increase of emotion “under control”.

Increase of A and decrease of V and D in group 3-1-1 and group 3-3-1, makes photo more scary.

2. Adding noise to the image (increase of corners)

Decrease of A in group 3-1-1 and group 3-3-1, makes photos less scary. Changes in other groups are not obvious.

In adjustments 3,4 affects opposes each other such that decrease of maximum makes photos of group 1-1-1 and group1-2-1 to be more pleasant, that of group 2-2-1 and group 2-2-3 to be more controllable and that of group 3-1-1 and group3-3-1 to be less scary. Increases of minimum bring reverse results.

VIII. CONCLUSIONS

As the result of input evaluation for training phase, the following points can be considered as achievements. The results suggest that a considerable accuracy could be achieved even with the missing of content based information.

1. As the rgb4scale proved to be accurate than the rest. This confirms the contribution of color when selecting input parameters.
2. The gray4scale could be useful during practical applications such as unifying the data into gray scale to avoid unnecessary color interferences.
3. The 4 parameters improve the training accuracy.
4. The affect test suggest that the sharpening accelerates affects in many groups while adding noise showed a reverse affect on scary photos only. Adjustments of maximum and minimum change the brightness of photo and changes histogram greatly.

Finally it can be stated that if a photo set can be classified within a certain affective range, the trained neural network with rgb4 scale has a good predictive ability of emotional vector value.

As a further research prospective to increase training accuracy, change the ratio of each sector of a particular scale can be considered.

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