Emotion recognition from posed and spontaneous dynamic expressions:

Human observers vs. machine analysis

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Abstract

The majority of research on the judgment of emotion from facial expressions has focused on deliberately posed displays, often sampled from single stimulus sets. Herein, we investigate emotion recognition from posed and spontaneous expressions, comparing classification performance between humans and machine in a cross-corpora investigation. For this, dynamic facial stimuli portraying the six basic emotions were sampled from a broad range of different databases, and then presented to human observers and a machine classifier. Recognition performance by the machine was found to be superior for posed expressions containing prototypical facial patterns, and comparable to humans when classifying emotions from spontaneous displays. In both humans and machine, accuracy rates were generally higher for posed compared to spontaneous stimuli. The findings suggest that automated systems rely on expression prototypicality for emotion classification, and may perform just as well as humans when tested in a cross-corpora context.

Keywords: spontaneous, facial expression, emotion, dynamic, machine analysis

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Most past work on the perception of emotional expressions has relied on posed or acted facial behavior, often depicted in a static position at or very near the peak of an expression. Deliberately posed displays allow for good recognizability (e.g., Ekman, Friesen, & Ellsworth, 1972). However, due to their idealized and often exaggerated nature, they may be unrepresentative of spontaneous affective expressions commonplace in everyday life. Herein, we seek to assess emotion recognition from posed and spontaneous dynamic expressions, comparing classification performance between humans and machine.

Apart from their higher ecological validity, spontaneously displayed expressions often contain complex action patterns which can increase the ambiguity of their emotional content (Cohn, Ambadar, & Ekman, 2007). As a result, recognition accuracy has been argued to drop as spontaneous expressions move farther away from prototypical, stylized representations of an emotion (e.g., Motley & Camden, 1988; Naab & Russell, 2007; Nelson & Russell, 2013; Wagner, MacDonald, & Manstead, 1986, for a review see Calvo & Nummenmaa, 2016). Nonetheless, recent work points towards mixed evidence regarding the recognizability of posed and spontaneous expressions (Abramson, Marom, Petranker, & Aviezer, 2017), and suggests that the result may depend on the specific stimulus set used (Sauter & Fischer, 2018). The latter point is particularly pertinent in the context of automated facial expression analysis (AFEA).

Many machine-based systems have been trained on a few - often posed/acted - datasets (Pantic & Bartlett, 2007), raising concerns about their ability to generalize to the complexity of expressive behavior in spontaneous and real-world settings. Moreover, past efforts typically relied on in-house techniques for affect recognition. Given that AFEA is nowadays widely accessible, emotion classification using publicly/commercially available software

(e.g. FaceReader, CERT, FACET) is of increasing research interest. Such software was recently found to perform similarly well (and often better) than human observers for prototypical facial expressions of standardized datasets (Del Lábano, Calvo, Fernández-Martín, & Recio, 2018; Lewinski, den Uyl, & Butler, 2014), but worse for subtle expressions that were non-stereotypical (Yitzhak et al., 2017) or produced by laypeople in the laboratory (Stöckli, Schulte-Mecklenbeck, Borer, & Samson, 2017). In none of the above studies, however, emotion recognition was tested in spontaneous affective displays.

The present research aims to fill this knowledge gap by investigating human and machine emotion recognition performance in posed *and* spontaneous facial expressions. It does so by providing cross-corpora results in which stimuli are sampled from a broad range of different databases. These include expressive behaviors ranging from directed or enacted portrayals (posed) to emotion-induced responses (spontaneous). Importantly, all of them contain dynamic expressions which are key to the differentiation between posed and spontaneous displays (Krumhuber, Kappas, & Manstead, 2013; Zloteanu, Krumhuber, & Richardson, 2018). Following common approaches, we focused on the classification of facial expressions portraying the six basic emotions. Instead of a single forced-choice task (which has been heavily criticized because it forces observers to choose a single emotion, Russell, 1993), participants indicated the relative extent of occurrence for multiple emotion categories of the same expression, thereby allowing maximum comparability to the machine recognition data.

Based on previous research pointing towards superior emotion classification from posed relative to spontaneous displays (Motley & Camden, 1988; Nelson & Russell, 2013), we predicted that recognition accuracy of posed expressions generally exceeds that of spontaneous ones; a finding which may be explained by the frequent occurrence of prototypical facial patterns when behavior is posed. Higher emotional prototypicality might

further facilitate AFEA (e.g. Yitzhak et al., 2017), with the result that the machine performs better (or equally well) compared to humans in classifying emotions from posed expressions, while recognition accuracy should be similar (or worse) in the context of spontaneous expressions.

Method

Stimulus Material

Dynamic facial expressions in the form of video-clips were taken from 14 databases, and featured single person portrayals of at least four basic emotions (see Table S1). Nine of the databases contained posed facial expressions, emerging from instructions to perform an expression/facial action or scenario enactments. Five databases included spontaneous facial expressions that had been elicited in response to emotion-specific tasks or videos (for a review see Krumhuber, Skora, Küster, & Fou, 2017). For the purpose of the present study, we focused on the six basic emotions - anger, disgust, fear, happiness, sadness, surprise - as predefined by the dataset authors.¹ Two exemplars of each emotion category were randomly selected from every database, yielding 12 emotion portrayals per database. The two exceptions were DISFA and DynEmo, both of which contain only five and four of the basic emotions, respectively. This resulted in a total of 162 dynamic facial expressions (54 spontaneous, 108 posed) from 85 female and 77 male encoders. Stimuli lasted on average 5 s and were displayed in color (642 x 482 pixels).²

Human Observers

Participants. Seventy students (79% females) aged 18-24 years ($M = 19.61$, $SD = 1.57$) were recruited, ensuring 85% power to detect a small-sized effect (Cohen's $f = .18$, $\alpha = .05$ two-tailed, $r = 0.8$) in a 2 (Machine vs. Human) x 2 (Posed vs. Spontaneous) x 6 (Emotion) within-between subjects repeated measures ANOVA. Participants were

predominantly of White/Caucasian ethnicity (96%). Ethical approval was granted by the Department of Experimental Psychology, UCL.

Procedure. Participants were randomly presented with one of two exemplars of each emotion category from every database, netting 81 dynamic facial expressions per participant. Stimulus sequence was randomized using the Qualtrics software (Provo, UT), with each video-clip being played only once. For each facial stimulus, participants rated their confidence (from 0 to 100%) about the extent to which the expression reflected anger, disgust, fear, happiness, sadness, surprise, other emotion, and neutral (no emotion). If they felt that more than one category applied, they could respond using multiple sliders to choose the exact confidence levels for each response category. Ratings across the eight response categories had to sum up to 100%.

Machine Analysis

All video stimuli were submitted to automated analysis by means of FACET (iMotions, SDK v6.3). FACET is a commercial software for automatic facial expression recognition, originally developed by the company Emotient (based on the Computer Expression Recognition Toolbox (CERT) algorithm, Littlewort et al., 2011). FACET codes facial expressions both in terms of FACS Action Units (AU) as well as the 6 basic emotions. For details regarding the measurement of machine classification performance see the Supplementary Materials.

To assess the occurrence of emotion prototypes as predicted by Basic Emotion Theory (Ekman et al., 2002, p. 174), AU combinations indicative of full prototypes or major variants (comprising more lenient criteria) were scored as 1 or 0.75, respectively. We further calculated a weighted prototypicality score by summing the FACET confidence scores of AUs within a combination, and multiplying the sum scores by 1 (full prototype) or 0.75

(major variant). This resulted in a total prototype score, with higher numbers reflecting greater emotional prototypicality.

Results

Recognition confidence scores were calculated for the two exemplars of each emotion category from every database which served as the unit of analysis.³ The mean target emotion recognition of 54.83% ($SD = 27.84$) for human observers and 61.91% ($SD = 41.52$) for machine analysis was significantly higher than chance, set conservatively at 25%, $t_{human}(161) = 13.64, p < .001, d = 1.07, 95\% \text{ CI } [25.51, 34.16]$; $t_{machine}(159) = 11.24, p < .001, d = 0.89, 95\% \text{ CI } [30.43, 43.40]$ (Frank & Stennett, 2001). Overall, FACET outperformed human observers in target emotion classification, $Z = 2.70, p = .007, r = .21, 95\% \text{ CI } [1.06, 13.53]$.⁴

When comparing recognition performance separately for posed and spontaneous expressions, results revealed a significant human vs. machine difference in the context of posed ($M_{human} = 61.95, SD = 25.17$ vs. $M_{machine} = 69.82, SD = 38.12$), $Z = 2.67, p = .008, r = .26, 95\% \text{ CI } [0.01, 15.73]$, but not spontaneous expressions ($M_{human} = 39.40, SD = 27.20$ vs. $M_{machine} = 45.49, SD = 43.81$), $Z = 0.79, p = .428, r = .11, 95\% \text{ CI } [-4.35, 16.54]$.

An analysis of the emotion prototype scores showed that posed portrayals were more prototypical in their facial AU patterns than spontaneous ones, $U = 1980.5, p = .002, r = .24, 95\% \text{ CI } [5.14, 24.68]$ (see Figure 1 for mean prototype frequencies). This applied to all emotions ($Us < 52, ps < .081$) except for happiness whose prototypicality didn't differ as a function of elicitation condition ($U = 57, p = .217, r = .24, 95\% \text{ CI } [-30.78, 8.38]$). A regression analysis revealed that the prototypicality of an expression significantly predicted the machine advantage over humans in emotion classification, $\beta = .287, t(158) = 2.78, p = .006, 95\% \text{ CI } [0.08, 0.49]$.

In both humans and machine, emotion recognition accuracy was on average higher for posed than spontaneous expressions, $U_{human} = 1654$, $p < .001$, $r = .35$, 95% CI [12.76, 29.90]; $U_{machine} = 2036$, $p = .004$, $r = .23$, 95% CI [10.23, 38.43]. As shown in Figure 2, this performance advantage applied to posed expressions of anger (human: $U = 9$, $p = .003$, $r = .61$, 95% CI [18.45, 68.00]), disgust (machine: $U = 48$, $p = .088$, $r = .33$, 95% CI [5.11, 57.22]), sadness (human: $U = 21$, $p = .005$, $r = .56$, 95% CI [10.74, 51.15]; machine: $U = 16$, $p = .001$, $r = .63$, 95% CI [33.31, 93.30]), fear (human: $U = 34$, $p = .007$, $r = .51$, 95% CI [8.23, 44.42]; machine: $U = 29$, $p = .003$, $r = .55$, 95% CI [9.73, 68.34]), and surprise (human: $U = 34$, $p = .007$, $r = .51$, 95% CI [8.78, 46.07]). Also, human observers made less use of the categories ‘other emotion’, $U = 2256.5$, $p = .019$, $r = .18$, and ‘neutral’, $U = 2001$, $p = .001$, $r = .26$, when rating posed than spontaneous expressions.

In order to quantify the similarity of confusions between machine and human, each matrix was transformed into a single vector (see Kuhn et al., 2017). Correlational analyses indicated a significant overlap between both matrices for posed expressions ($\rho = .637$, $S = 2818$, $p < .001$) and spontaneous expressions ($\rho = .598$, $S = 3123.8$, $p < .001$), suggesting that recognition patterns of target and non-target emotions were positively related in humans and machine.

Discussion

In this paper, we sought to compare emotion recognition rates from posed and spontaneous dynamic expressions. Rather than relying on single stimulus sets as done previously, numerous dynamic databases were employed that feature a variety of expression elicitation techniques. Whilst the small number of chosen stimuli per dataset may not be representative of the full database, we think that this approach importantly allows for a cross-corpora evaluation of posed and spontaneous expressions.

In accordance with prior findings (e.g. Motley & Camden, 1988), posed expressions were better recognized than spontaneous ones. Also, facial patterns were more prototypical in posed displays, which made classification by the machine highly successful. Similar to Yitzhak et al. (2017), FACET outperformed humans in the context of posed datasets; a recognition advantage which was driven by the prototypicality of expression. Hence, AFEA based on specific configurations of prototypical facial activity appears to be sufficiently robust (Zeng, Pantic, Roisman, & Huang, 2009). Although performance dropped when the stimuli were spontaneous, accuracy rates and confusion patterns were similar for humans and machine. This is an important finding as it suggests that AFEA can be equally sensitive to spontaneously occurring behavior (Bartlett et al., 2005).

To allow for a variety of potential interpretations of facial expressions, in the current study human observers could select multiple emotion labels as well as no/other emotion. Besides avoiding potential artifacts observed with forced-choice tasks (Frank & Stennett, 2001), the chosen approach was shown to reveal results that were similar to traditional paradigms without additional response options (see Supplementary Materials). Nonetheless, in the future it would be important to equate the number of response categories by presenting only six emotion terms. Also, a larger amount of portrayals could be included, potentially aiming for a full validation of the 14 dynamic sets. This may also provide a benchmark for comparison between different automated methods of measuring facial expressions. The present study provides the first evidence suggesting that computer-based systems perform as well as (and often better than) human judges in affect recognition from facial expressions sampled from a broad range of databases.

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Footnotes

¹ Due to lack of uniformity in emotion labelling across databases, amusement (BINED, DynEmo) and joy (ADFES, DISFA, GEMEP) were included under the umbrella of happiness. In one database (MPI), missing portrayals of surprise were substituted with those of disbelief, belonging to the same emotion family (Shaver, Schwartz, Kirson, & O'Connor, 1987). Action Unit configurations characteristic of the six basic emotions as proposed in the Facial Action Coding System manual (FACS, Ekman, Friesen, & Hager, 2002) were selected in the context of the D3DFACS database which itself does not include emotion labels.

² Portrayals that lasted longer than 15 s (BINED, DynEmo) were edited to display the emotional peak of the expression from onset (neutral face), through apex, to offset (if applicable), resembling portrayals from the majority of databases. None of the final facial stimuli exceeded 10 s in duration.

³ Two portrayals (one happy, one disgust) from the BINED database could not be processed by FACET. For six cases in which the evidence values for both target and non-target emotions were below the set threshold (< 0), equal weightings were assigned to the six response options of a portrayal.

⁴ A 2 (Machine vs. Human) x 2 (Posed vs. Spontaneous) x 6 (Emotion) ANOVA revealed a significant three-way interaction, $F(5, 148) = 3.29, p = .008, \eta_p^2 = .10$. This effect remained significant when portrayer gender and video duration were entered as covariates, $F(5, 146) = 3.21, p = .009, \eta_p^2 = .10$. Non-parametric tests were used to analyze human vs. machine differences in recognition performance (due to violations of the assumption of homogeneity of variance) and when comparing posed vs. spontaneous expressions (due to unequal cell sizes).

Figure 1. Mean frequency (as indicated by the density plot width) of facial emotion prototypes in posed and spontaneous expressions.

Figure 2. Confusion matrices of emotion categorization for human observers and FACET machine classifier averaged across dataset exemplars for posed and spontaneous expressions of each basic emotion.

Supplementary Materials

Emotion recognition from posed and spontaneous dynamic expressions: Human observers vs. machine analysis

By E. G. Krumhuber, D. Küster, S. Namba, S. Datin, & M. G. Calvo

Method for Machine Analysis

The FACET software outputs per-frame evidence values (in odds ratios) for each emotion (anger, disgust, fear, happiness, sadness, surprise) and AU category (AU1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 18, 20, 23, 24, 25, 26, 28, 43) which reflect estimates of the likelihood of an expression/AU in a given stimulus. Evidence values typically range from -4 to +4, with values > 0 indicating higher probability that the expression/AU is present. FACET provides no guidelines for the aggregation of frame-level data in videos. In the present case, we opted to preserve the relative weight of evidence within a video for each expression/AU rather than e.g. selecting evidence maxima. We therefore aggregated all per-frame evidence values using the following formula proposed by Dente, Küster, Skora, & Krumhuber (2017) to measure machine classification performance:

$$\text{Confidence} = \frac{\sum_{i=1}^n x_i}{\sum_{i=1}^n x_i + \sum_{i=1}^n y_i} * 100$$

Recognition confidence reflects the proportion of all evidence for a given expression/AU (x, e.g. happiness) above a set threshold (> 0) relative to the total above-threshold evidence for all expressions together (consisting of the evidence for the given expression (x; e.g. happiness) and evidence for all other expressions (y; e.g. anger, disgust, fear, sadness, surprise)). The proportion is then multiplied by 100 to produce a percentage score (from 0 to 100%) which represents the degree to which an emotional expression/AU is displayed in the face.

While several other metrics exist to aggregate per-frame data (e.g., means, maxima, area under the curve), most of them fail to take into account the ability of human judges to view any individual expression as meaningful within the context of other facial activity being shown in a given video. Hence, for humans an equal absolute amount of evidence for a given expression (e.g., happiness) may result in different ratings depending on the perceived relative presence of other expressions throughout a given video. The metric used in this research is more robust than recognition sensitivity (hit rates) as it takes into account false-positive classifications, even for those evidence scores that are minimally above the set threshold.

Additional Results

Consistent with past work (Palermo & Coltheart, 2004), happiness was the best recognized facial expression in both human observers and machine, followed by disgust and surprise, then anger or sadness, and lastly fear. Post-hoc comparisons (Bonferroni corrected) revealed significant differences between happiness and the other emotions, i.e. anger ($p_{human} = .001$, $p_{machine} = .003$), fear ($p_{human} < .001$, $p_{machine} = .001$), sadness ($p_{human} = .010$, $p_{machine} = .002$), and surprise ($p_{machine} = .016$); and between fear and the other emotions, i.e. surprise ($p_{human} < .001$), disgust ($p_{human} < .001$), and sadness ($p_{human} = .030$). Except for fear which was often confused with surprise in human observers ($p = 1.00$; see also Abramson et al., 2017), target emotion ratings were significantly higher than non-target ratings ($ps < .01$).

An analysis by the type of classifier (machine vs. human) and expression (posed vs. spontaneous) revealed that the machine achieved higher recognition confidence rates than humans for the majority of posed emotional expressions. This was significant for happiness, $Z = 2.94$, $p = .003$, $r = .69$, 95% CI [3.23, 21.96]; disgust: $Z = 2.24$, $p = .025$, $r = .53$, 95% CI [3.21, 33.18]; and fear: $Z = 2.03$, $p = .043$, $r = .48$, 95% CI [1.40, 44.01]. In the context of

spontaneous expressions, performance by the machine was better for classifying happiness, $Z = 2.55, p = .011, r = .85, 95\% \text{ CI } [8.50, 43.88]$, but worse than humans for classifying sadness, $Z = 2.52, p = .012, r = .89, 95\% \text{ CI } [-37.01, -12.72]$. All other differences were non-significant ($Z_s < 1.58, p_s > .115$).

Figure S1. FACET confidence scores of individual Action Units (AU) for posed and spontaneous expressions of each basic emotion. AUs which are predicted to signal a particular emotion according to Basic Emotion Theory (Ekman et al., 2002) are printed in bold.

Inspection of Figure S1 suggests that posed expressions exhibited greater emotional prototypicality than spontaneous expressions. For the majority of emotions, this is evidenced by the higher confidence scores of key AUs that are characteristic of an emotion prototype. The extent to which an AU configuration is prototypical could therefore help to explain why posed expressions were highly recognizable by a machine classifier that was trained on

prototypical facial expressions (Pantic & Bartlett, 2007). Furthermore, compared to spontaneous expressions we observed generally less widespread activation of other non-prototypical AUs whose blended patterns of facial activity may have led to poorer emotion recognition performance in both humans and machine.

When comparing humans vs. machine in emotion recognition, it is important to understand that software tools such as FACET focus on visual/perceptual information (i.e. AU configurations), whereas human observers rely more on contextual and affective information (Calvo & Nummenmaa, 2016). Such underlying differences in human and machine approaches to expression analysis become most apparent in the context of spontaneous expressions. For example, a brief glimpse of a frown (600 ms) that appears on an otherwise non-expressive face during a 4 s video might be classified as anger by humans, but as neutral by conventional computer systems (that perform pre-trained per-frame classifications) because no distinct facial activity was visible most (85%) of the time (see Table 1 in Yitzhak et al., 2017, for an illustration of this point). As FACET provides no inbuilt sequential modelling mechanism for neutral frames, we decided against the inclusion of a ‘neutral’ response category in the machine classification.

To equate the number of emotion categories across humans and machine, we ran additional analyses in which we post-experimentally removed the ‘neutral’ response option from the human data. This strategy was further supported by the fact that neutral videos were not part of the present research question. When ‘neutral’ was removed as a response category in human observers, the pattern of results remained the same. That is, the machine outperformed humans in classifying emotions from posed expressions ($M_{\text{machine}} = 69.82$, $SD = 38.12$ vs. $M_{\text{human}} = 65.30$, $SD = 25.29$), $Z = 2.06$, $p = .039$, $r = .20$, while recognition accuracy was similar in the context of spontaneous expressions ($M_{\text{machine}} = 45.49$, $SD = 43.81$ vs.

$M_{\text{human}} = 46.38$, $SD = 27.72$), $Z = 0.19$, $p = .848$, $r = .02$. The prototypicality of an expression significantly predicted the machine advantage over humans in emotion classification accuracy, $\beta = .329$, $t(158) = 3.14$, $p = .002$. This regression remained significant when both ‘neutral’ and ‘other’ were excluded as response categories, $\beta = .362$, $t(158) = 3.44$, $p = .001$. In the latter case, the mean prototype frequencies were found to significantly predict the machine advantage over humans for posed, $\beta = .213$, $t(106) = 2.24$, $p = .027$, but not spontaneous expressions, $\beta = .111$, $t(50) = 0.79$, $p = .435$.

To address further concerns regarding the inclusion of a ‘neutral’ and ‘other’ category in human ratings, we collected additional data with a new sample of participants. For this, forty-three Amazon Mechanical Turk workers (Buhrmester, Kwang, & Gosling, 2011) were recruited online and participated in exchange for \$7.00. Three participants failed an in-built manipulation check (Oppenheimer, Meyvis, & Davidenko, 2009), leaving a total of 40 participants (25 males; $M_{\text{age}} = 33.63$ years, $SD = 9.19$). The majority (75%) identified themselves as White, followed by 12.5% Asian, 7.5% African, 2.5% Hispanic, and 2.5% other. The study was conducted with ethical approval from the Department of Experimental Psychology at University College London, United Kingdom. The stimulus material and procedure were the same as in the main experiment, except that the number of response categories was limited to the six basic emotion terms. Because no alternative options such as ‘other’ or ‘none of the above’ were available, participants were encouraged to provide their responses on multiple dimensions, particularly when they felt that more than one emotion label could be applied. In line with previous findings, the machine outperformed humans in classifying emotions from posed expressions ($M_{\text{machine}} = 69.82$, $SD = 38.12$ vs. $M_{\text{human}} = 53.00$, $SD = 16.69$), $Z = 3.90$, $p < .001$, $r = .38$, while recognition accuracy was similar in the context of spontaneous expressions ($M_{\text{machine}} = 45.49$, $SD = 43.81$ vs. $M_{\text{human}} = 40.55$, $SD = 19.26$), $Z = 0.72$, $p = .472$, $r = .10$. The prototypicality of an expression significantly

predicted the machine advantage over humans in emotion classification accuracy, $\beta = .334$, $t(158) = 4.46$, $p < .001$. When analysed by the type of expression, the mean prototype frequencies were found to significantly predict the machine advantage over humans for posed, $\beta = .252$, $t(106) = 2.68$, $p = .008$, but not spontaneous expressions, $\beta = .194$, $t(50) = 1.40$, $p = .168$.

Together, these findings suggest that the higher performance of the machine classifier in recognizing posed expressions based on prototypical AU configurations persists even when ‘neutral’ and ‘other’ are eliminated from the list of human responses. As such, adding a ‘none’ or ‘other’ escape option does not change the overall level of target emotion recognition; a result which is in accordance with research by Frank and Stennett (2001, Experiment 1). It is therefore unlikely that the provision of these categories in the main experiment disadvantaged human observers in choosing the correct emotion label.

Table S1

Stimulus file names of 162 videos as used in this research

Database	Emotion	Stimulus ID
ADFES (posed)	anger	medit_F08-Anger-Face_Forward north_europ_M04-Anger-Face_Forward
	disgust	medit_F10-Disgust-Face_Forward north_europ_F03-Disgust-Face_Forward
	fear	medit_M07-Fear-Face_Forward north_europ_M11-Fear-Face_Forward
	happiness	medit_F06-Joy-Face_Forward north_europ_M08-Joy-Face_Forward
	sadness	medit_M01-Sadness-Face_Forward north_europ_F01-Sadness-Face_Forward
	surprise	medit_M10-Surprise-Face_Forward north_europ_F04-Surprise-Face_Forward
BINED (spontaneous)	anger	f37s7 anger m23z7 anger
	disgust	f4511 disgust m40t6 disgust
	fear	m6r3 fear m11p3 fear
	happiness	f07m8 amusement m15d8 amusement
	sadness	f09s5 sadness m1k5 sadness
	surprise	f13d2 surprise m4k2 surprise
BU-4DFE (posed)	anger	F027_Angry M005_Angry
	disgust	F001_Disgust M019_Disgust
	fear	F005_Fear M036_Fear
	happiness	F049_Happy M032_Happy
	sadness	F006_Sad M014_Sad
	surprise	F051_Surprise M042_Surprise
CK (posed)	anger	S0117 - 006 S0504 - 001
	disgust	S046 - 004 S081 - 008
	fear	S067-003 S0501 - 004
	happiness	S044 - 003

		S070 - 003
	sadness	S107 - 006
		S0503 - 006
	surprise	S011 - 001
		S089 - 001
D3-DFACS (posed)	anger	Joe_AU4+5
		Kornelia_AU4+5
	disgust	Darren_AU9+10+25
		Kornelia_AU9+10+25
	fear	Darren_AU1+2+4+5+11+38
		Eva_AU1+2+4+5
	happiness	Adrian_AU12+25
		Helen_AU6+12+25
DaFEx (posed)	sadness	Joe_AU1+4
		Michaela_AU1+4+11
	surprise	Adrian_AU1+2+5
		Michaela_AU1+2+5
DISFA (spontaneous)	anger	act 1 - blk 1 - ang - mid
		act 8 - blk 4 - ang - mid
	disgust	act 3 - blk 5 - dis - mid
		act 7 - blk 6 - dis - mid
	fear	act 4 - blk 2 - fea - mid
		act 6 - blk 2 - fea - mid
	happiness	act 2 - blk 3 - hap - mid
		act 4 - blk 4 - hap - mid
DynEmo (spontaneous)	sadness	act 3 - blk 4 - sad - mid
		act 5 - blk 4 - sad - mid
	surprise	act 1 - blk 5 - sur - mid
		act 5 - blk 1 - sur - mid
FG-NET	disgust	LeftVideoSN012_comp
		LeftVideoSN026_comp
	fear	LeftVideoSN011_comp
		LeftVideoSN32_comp
	happiness	LeftVideoSN002_comp
		LeftVideoSN025_comp
	sadness	LeftVideoSN016_comp
		LeftVideoSN018_comp
DVD2	surprise	LeftVideoSN004_comp
		LeftVideoSN005_comp
	disgust	DVD2_5
		DVD28_4
DVD21	fear	DVD21_2
		DVD29_4
	happiness	DVD11_1
		DVD13_5
DVD12	surprise	DVD12_3
		DVD22_4
anger_0006_2	anger	anger_0006_2

(spontaneous)		anger_0018_3
	disgust	disgs_0003_3 disgs_0018_3
	fear	fears_0009_2 fears_0013_3
	happiness	happy_0005_2 happy_0011_2
	sadness	sadns_0007_2 sadns_0015_2
	surprise	surpr_0003_3 surpr_0015_2
GEMEP (posed)	anger	01ang_Gemep 06ang_Gemep
	disgust	02dis_Gemep 05dis_Gemep
	fear	04fea_Gemep 10fea_Gemep
	happiness	04joy_Gemep 09joy_Gemep
	sadness	05sad_Gemep 10sad_Gemep
	surprise	07sur_Gemep 08sur_Gemep
MMI (posed)	anger	S002-099 S032-001
	disgust	S001-104 S015-002
	fear	S031-004 S040-005
	happiness	S046-010 S047-007
	sadness	S001-114 S042-007
	surprise	S005-109 S036-003
MPI (posed)	anger	jakm_ang_rep001_cam003_sub002_im_40 mamm_ang_rep002_cam003_sub002_im_40
	disgust	lekf_disg_rep001_cam003_sub002_im_40 milf_disg_rep001_cam003_sub002_im_40
	fear	jakm_feter_rep002_cam003_sub002_im_40 silf_feshit_rep003_cam003_sub002_im_40
	happiness	mamm_halau_rep003_cam003_sub002_im_40 silf_halau_rep001_cam003_sub002_im_40
	sadness	cawm_sad_rep001_cam003_sub002_im_40 lekf_sad_rep001_cam003_sub002_im_40
	surprise	cawm_disb_rep001_cam003_sub002_im_40 silf_disb_rep002_cam003_sub002_im_40
STOIC	anger	DF3an

(posed)		DM1an
	disgust	DM4di
		DM5di
	fear	DF5fe
		DM3fe
	happiness	DF4ha
		DM2ha
	sadness	DF1sa
		DF5sa
	surprise	DF1su
		DF2su
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UT-Dallas	anger	04518v117
(spontaneous)		04661v117
	disgust	04807v116
		04810v116
	fear	04536v115
		04619v115
	happiness	04531v113
		04543v113
	sadness	04630v114
		04640v114
	surprise	03520v128
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