http://dx.doi.org/10.1145/2559206.2581205

How is your laugh today?

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CHI 2014, Apr 26 - May 01 2014, Toronto, ON, Canada

DOI http://dx.doi.org/10.1145/2559206.2581205

Abstract
Despite its relevance for human-human communication, laughter has been quite under-investigated and under-exploited in human-machine interaction. Nevertheless, endowing machines with the capability of analyzing laughter (i.e., to detect when the user is laughing, to measure intensity of laughter, to distinguish between different laughter styles and types) in ecological contexts is a very challenging task. An approach to laughter recognition consisting in the real-time analysis of a single communication modality, i.e., body, is presented in this paper and positive results of an evaluation study are discussed.

Author Keywords
laughter detection; body movement analysis;

ACM Classification Keywords
H.5.m. [Information Interfaces and Presentation (e.g. HCI)]: Miscellaneous

Introduction
Leonard is in a particularly stressing period: he recently moved to another country, he has some strict deadlines to meet, he feels frustrated and nervous about his situation. So his new colleagues and friends invite him to spend some time watching funny movies and playing amazing

Figure 1: Input RGB and depth images are pre-processed to isolate user's head, trunk, arms and to track shoulder's markers.

board games, laughing together a lot. Indeed, the positive effects of laughter listed above have already been observed and measured, e.g., in [12][3]. Also, social contexts could facilitate eliciting laughter [14]. He then decides to probe whether laughter could be automatically elicited and detected by machines. Beside monitoring user's physical and psychological state, such "laughter-sensitive" machines could be used to elicit and measure user's laughter by involving her in funny activities.

This is a very challenging task which is starting to be addressed by researchers, see for example the EU Project ILHAIRE (www.ilhaire.eu) on laughter detection and synthesis. It is noteworthy to take into account that: laughter is highly multimodal; in social context such multimodality could affect laughter detection (e.g., distinguishing and analyzing users' voices in multi-party interaction is an open challenge; facial activity can not be tracked in ecological contexts); it is not clear if it is possible to distinguish different types of laughter, both at general (e.g., ironic , fearful) and individual (e.g., introvert, extrovert) level, from expressive or morphological multimodal features. The presented study consists in the real-time automated analysis of laughter intensity from a single modality, that is, body movement. It differentiates from previous work on laughter recognition that focus on other/multiple modalities [7][15]. Recently, it was shown that it is possible to distinguish laughter only from body movement [9]. Intensity has been chosen as it is an expressive characteristic that can be evaluated for any laughter type. This is a work-in-progress, further expressive characteristics of laughter, such as up/down-regulation, will be addressed with the same approach as intensity, allowing researchers to overcome the issues about laughter listed above and, in a long-term view, to build "laughter-sensitive" machines.

The approach presented in the remainder of this paper is based on computer vision and machine learning. First, the position of significant body parts in laughter are extracted from input video streams. Then, low level body features describing laughter are computed. Finally, 2 neural networks are applied: the first one distinguishes between laughter and non-laughter; the second one measures laughter intensity on a 4 steps scale.

Body Laughter Features

Body and its movements are important indicators of laughter which have been widely neglected in the past. Ruch and Ekman [17] observed that laughter is often accompanied by one or more (i.e., occurring at the same time) of the following body behaviors: "rhythmic patterns", "rock violently sideways, or more often back and forth", "nervous tremor ... over the body", "twitch or tremble convulsively". Becker-Asano and colleagues [2] observed that laughing users "moved their heads backward to the left and lifted their arms resembling an open-hand gesture". Markaki and colleagues [11] analyzed laughter in professional (virtual) meetings: the user laughs "accompanying the joke's escalation in an embodied manner, moving her torso and laughing with her mouth wide open" and "even throwing her head back".

Preprocessing

Body laughter features extraction is currently carried out starting by: (i) RGB video captured by a webcam 640x480 @ 30 fps (upper panel of Figure 1); (ii) BW depth map video (each pixel is a 16 bit value indicating the distance from camera) captured by Kinect 640x480 @ 30 fps (middle panel of Figure 1); (iii) two green polystyrene markers on user's shoulders. The data are captured and processed in real-time using the Eyesweb XMI software [16][10]. Shoulder's markers are automatically extracted

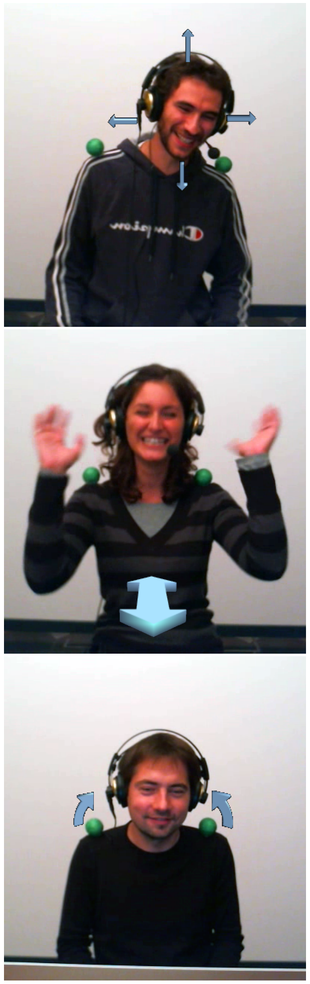

Figure 2: From top to bottom: trunk, head, shoulder features examples.

by thresholding the RGB video components. Similarly, the user's silhouette is automatically thresholded the depth map video. The green markers' position helps to separate head from trunk and arms in the user's silhouette. Webcam video processing is necessary because Kinect SDKs (e.g., OpenNI, Microsoft) fail to detect changes of shoulder's position during shoulder trembling, as it has been tested by authors. The final result of the process, that is, the areas labeled **H**, **T**, **A1**, **A2**, is shown in the lower side of Figure 1. These areas have been considered in previous studies on laughter body movement [9].

Head features

Head algorithms start from the head's silhouette, that is, the region labeled **H**. The CoG (Center of Gravity) of the region is detected and its 2D coordinates are extracted; CoG horizontal and vertical speed are computed. The maximum values of such speed over a 2 seconds time window are the body features *F1* and *F2*.

Trunk features

Among all the relevant body laughter features previously described, the focus is on: (i) trunk *leaning*, that is, a slow, wide and repetitive front/back or side-to-side movement of trunk; (ii) trunk *throwing*, that is, a quick, abrupt and non-repetitive front/back or side-to-side movement of trunk. Trunk algorithm starts from a comparison between head's and trunk's silhouette distance from the camera. These distances are provided by the depth image segmentation carried out during preprocessing. More specifically, the difference D between the averaged distances of areas **H** and **T** is computed. Then, the standard deviation of D over a 2 seconds time window is used as a first hint of trunk leaning/throwing. If such a kind of movement is present then the following trunk features are extracted:

- *F3* is the periodicity of D; it is high if a prominent frequency is detected in D, it is low otherwise;
- *F4* is the amplitude of D;
- *F5* is the impulsiveness of D, that is, the ratio between the prominent peak amplitude in D and the duration of movement as described in [5];

Shoulder features

Shoulder *trembling* is a quick and repetitive movement often displayed by people during laughter, as described at the beginning of the section. Three shoulder features, based on shoulders' vertical coordinates $y1$ and $y2$, are extracted on a 2 seconds time window:

- *F6* the maximum value of Kinetic Energy, that is, the squared sum of both shoulders' vertical speed (i.e., 1st derivative $y1$ and $y2$);
- *F7* shoulders' correlation, that is, correlation between $y1$ and $y2$;
- *F8, F9* left/right shoulder's periodicity is high when a prominent frequency is detected in $y1$ and $y2$, it is low otherwise;

The above features are enabled whether trunk leaning is not detected, i.e., standard deviation of D is under a prefixed threshold. The threshold is computed by performing some preliminary sessions in which people are asked to perform trunk movements with variable speed. It seems reasonable to neglect time intervals in which shoulder movement is induced by trunk leaning back and forth.

Dataset and Annotation

Five participants were asked to participate in two different tasks: an individual one, that is, watching video clips alone; a social one, that is, playing a game called *yes/no*. The rules of the game are the following: the experimenter can ask the participant any questions and she is obliged to answer them without using any words “yes” and “no”. Choice of such tasks was inspired by the recent work of [13] where it is shown that they could successfully elicit laughter. Each participant performed each task in an experimental room equipped with a pc having internet connection, LCD screen, a webcam (640x480, 30 fps) and Kinect (640x480, 30 fps). The participant, sitting alone in front of the pc, wore a head mounted microphone, headphones and two green markers on her shoulders. At the beginning, the participant was invited (i) to play the yes/no game via Skype with one of the experimenters. Then, participant was asked (ii) to choose and watch from internet a very funny clip lasting about 4-6 minutes she liked (e.g., tv shows, clips from movies); (iii) to watch from the internet a very funny clip previously selected from the experimenters. Finally, participant had (iv) to play for a second time the yes/no game.

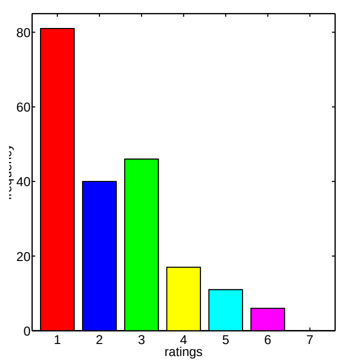

Figure 3: The histogram of the intensity ratings

All material was segmented (by considering multiple modalities such us facial expression and body movement) into 201 laughter segments and 164 non-laughter segments, respectively. Next, two experts on body movement analysis separately rated the intensity of each laughter segment by using a 7-points Likert scale from 1 to 7. The inter-rater agreement between raters was computed. The resulting weighted Cohen’s kappa indicated substantial agreement, k=0.78 [8] in laughter intensity ratings. Due to this substantial agreement, the provided ratings could be used as labels for gold standard in the performance evaluation of the classifier. When the ratings of a laughter segment differed between the two raters, the highest one was chosen as gold standard. Figure 3 depicts the histogram of the intensity ratings. The histogram shows strong imbalance: for example, only very few segments are rated 5 or 6, none segment was rated a 7. Building a classifier on such kind of data, the most frequent ratings (e.g., 1 and 2) would tend to prevail in the classification results. Consequently: (i) less frequent ratings were re-grouped following the schema showed by Table 1; (ii) a random sampling method was applied to the most frequent ratings.

Ratings	
Original	Re-mapped
1	1
2	2
3,4	3
5,6,7	4

Table 1: Re-mapping of laughter intensity rating.

Real-time automated detection

Two Kohonen's self-organising maps (SOMs) were trained with laughter and non-laughter instances extracted from the segments of the dataset. The first map is aimed at automatically recognising laughter from non-laughter, the second one is aimed at providing a classification of laughter intensity. The training instances consist of features F1-F9 computed on randomly picked segments of the dataset. Finally, each instance was standardised to have zero average and unitary standard deviation. Both SOMs consist in eight-by-eight rectangulary oriented units with codebook vectors randomly initialised with a number in the range $[0, 1]$. Training set were presented 900 times to each map, respectively. Learning rate and size of the neighborhood exponentially decrease, respectively, from 0.1 and 0.3 to 0 during the training.

Performance evaluation

To evaluate how well the SOMs classification matches the gold standard, that is, to provide accuracy of the maps, *Adjusted Rand Index (ARI)* [6] and *Adjusted Mutual Information (AMI)* [18] were computed on 100 bootstrapped instance sets. These measures, already adjusted for chance, range from 0 to 1, where 0 means chance class assignment and 1 means totally correct class assignment. Table 2 shows the averaged value of ARI and AMI and their standard deviation for each of the two SOMs, the laughter vs. non-laughter and the laughter intensity one. The overall results are promising because they are strongly above the chance threshold with a small standard deviation.

	ARI		AMI	
SOM	avg	std	avg	std
laughter/non-laughter	0.52	0.10	0.43	0.10
laughter intensity	0.44	0.05	0.49	0.04

Table 2: SOM Performance evaluation results

Conclusion and Future Works

A technique for automated laughter intensity detection from body movements, based on computer vision and machine learning, is discussed. Taking into account the preliminary nature of this work, results are promising: objective performance evaluation showed the validity of our approach. Use of dynamic analysis allowing to consider the temporal evolution of the laughter and its intensity over time is planned, through the use of, for example, HMMs. Nevertheless, results should be confirmed on a larger data-set containing, for example, recordings of people acting in different contexts when they laugh. Further, a limited number of laughter body movement features is here considered. Distinctive laughter styles and different laughter types have to be explored in collaboration with psychologists. In conclusion, it is worth noticing that the ability of detecting laughter and its characteristics would have much wider applications. For instance, several research show that people, when interacting with other humans [1], but also with virtual agents [4], adapt their behavior with the interlocutor by copying movements and/or movement features (e.g., speed/amplitude of gestures).

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