Towards multimodal expression of laughter

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Abstract. *Laughter is a strong social signal in human-human and human-machine communication. However, very few attempts to model it exist. In this paper we discuss several challenges regarding the generation of laughs. We focus, more particularly, on two aspects a) modeling laughter with different intensities and b) modeling respiration behavior during laughter. Both of these models combine a data-driven approach with high-level animation control. Careful analysis and implementation of the synchronization mechanisms linking visual and respiratory cues has been undertaken. It allows us to reproduce the highly correlated multimodal signals of laughter on a 3D virtual agent.*

Keywords: multimodal animation, expression synthesis, laughter, intensity

1 Introduction

Laughter is one of the most frequently used communicative signals. It is mostly associated with positive reactions to humorous stimuli, but it can also be a social signal such as an indicator of social position or relations [1] or even be a conversation regulator (e.g. such as a punctuator) [2]. Recent studies [3, 4] enumerate at least 23 different types of laughter such as angry, anxious, desperate, hysterical or contemptuous or sulky laughter. Laughter plays an important part in an interaction; it is a very contagious behavior [2]. It may also have a positive impact on health [5].

Humans are very sensitive to laughter. The social and communicative quality of laughter is crucial in human-human interaction. It is not surprising there is a new interest in laughter modeling for human-machine interaction, in particular when the machine takes the appearance of a virtual agent. Virtual agents might use laughter to communicate their intentions and social attitudes or to improve the relations with their human interlocutor. However, so far, there exist only few interactive systems ([6, 7], see Section 2) that make use of laughter and of its contagious effect. There are even fewer attempts of laughter synthesis.

Laughter is a highly multimodal expression in which different modalities are highly synchronized. In laughter, the body movements and the tight synchronization between audio and visual signals of the expression is crucial. Laughter is composed of very quick rhythmic shoulders and torso movements, visible inhalation, several facial expressions which are often accompanied with some rhythmic as well as communicative gestures [8]. Recent studies on laughter suggest that the various types of laughter may have different expressive patterns [4]. Consequently, even a small incongruence in laughter synthesis may influence its perception. This makes its synthesis particularly challenging. Careful attention needs to be put on the synchronization between modalities which seems to be a key factor to successful laughter synthesis. Thus laughter synthesis requires, first of all, a good understanding of the underlying physiological processes, the relations between the modalities as well as the communicative meanings of laughter cues.

Our long term goal is to build a virtual agent able to laugh believably and multimodally. In this paper we focus more particularly on the modeling of laughter visual intensity and on the respiration animation. In our approach we combine several existing animation techniques such as data-driven and procedural animation. In the remaining of this paper we present our model and the data we used.

This paper is structured as follows. The next section is dedicated to the description of the existing works on laughter synthesis. Then in Section 3 we discuss the challenges of the laughter synthesis. Next, we focus on two aspects of laughter: in Section 4 we present an approach for modulating perceived intensity of laughter while Section 5 is dedicated to the study and the animation of respiration during laughter. Finally we conclude the paper in Section 6.

2 State of art

Only few visual laughter synthesis models were proposed so far. In existing approaches the generation of laughter animation is often driven by some audio parameters. Cosker and Edge [9] propose a data-driven model for non-speech related articulations such as laugh, cries etc. The model based on HMM is trained from motion capture data and audio segments. First, the data are captured with the motion capture system Qualysis, with 30 markers placed on the face, and normalized to one chosen identity (i.e. one facial model). During the training phase, the model learns the correlations between the recoded audio and the visual data. For this purpose, the number of facial parameters is reduced using PCA, while MFCC is considered for the audio input.

DiLorenzo et al. [10] propose a physically-based parametric model of human chest that can be automatically driven from prerecorded audio laugh samples. The model uses an anatomically inspired and physics-based model of a human torso that is a combination of rigid-body and deformable components. It is based on the assumption that there exists a relation between lung pressure and the laughter phase that can be derived from the amplitude of the audio signal.

It takes into account the volume and lungs pressure, the air flow volume rate and the chest wall cavity. The model is restricted to the respiration during the laughter act; it does not involve other body moments. The animation is not generated in real-time.

While not directly related to laughter synthesis, some interesting works on respiration synthesis were proposed recently. De Melo et al. [11] study the role of respiration in expressing emotional states. Their respiration model is based on target morphing technique. They use 2 morph targets and morphing is applied to interpolate between these two targets. The model provides a set of parameters to control the respiration rate and depth. These parameters are manipulated manually to define the respiration profiles for 14 emotions. The evaluation shows that adding respiration improves significantly the perception of some emotions such as excitement, boredom or relief. Kider et al. [12] propose an anatomically inspired and data-driven model of human fatigue that includes, among others, respiration. The model is driven by data from different physiological sensors that control the visual appearance of a character. Regarding the respiration animation it uses an underlying anatomical model of the lungs. This approach is based on respiration sensor and on data on the vital capacity of lungs, expiratory reserve volume and tidal volume. Finally, the anatomical model of lungs is used to simulate realistic chest movement.

Recently laughter starts to play a more significant role in human-machine interaction. Urbain et al. [6] proposed the AudioVisualLaughterCycle machine, a system able to detect and respond to human laughs in real time. With the aim of creating an interaction loop between a human and an agent, the authors built a system capable of analyzing the user's laugh and of responding to it with a similar laugh produced by the virtual agent. This similar laugh is automatically chosen from an audio-visual laughter database. Its selection is done by measuring the acoustic similarities between the input laughter and the outputted one. The visual data corresponds to motion capture data of facial expressions. While the audio content of the similar laugh is directly replayed, the corresponding motion capture data is retargeted to a virtual model. Recently Fukushima et al. [7] built a system capable of increasing users' laughter reactions. It is composed of a set of toy robots that shake their heads and play prerecorded laughter sounds when the system detects user's laugh. An evaluation study shows that the system enhances users' laughing activity (i.e., it favors laugh contagion).

3 Laughter Synthesis

Laughter synthesis is a challenging task. A large quantity of movements occurs across modalities. Laughter is characterized by highly multimodal expressive patterns composed of different facial actions (see Section 4.1), head movements such as tilts, visible respiration (see Section 5.1), shaking of the shoulders, straighten or vibration of the trunk that are often completed with body inclinations, swinging, but also some gestures such as clapping hands or thighs [8]. The synchronization of all these modalities is critical. The preliminary audio-driven models of laughter described in the previous section are a first step towards the construction of a laughing virtual agent. However they often focus only on a single modality. Moreover their animation is not modifiable; e.g. it cannot be altered through an intensity parameter. These models still lack complete and time-efficient solution for body animation. In particular, compulsive chest and torso movements, which strongly contribute to laughter production, need to be captured and synthesized. At the same time capturing the data over the various modalities (face and body) at the same time is still considered a technical challenge. Hence, we believe it is important to develop an approach in which different modalities can be synthesized separately and then synchronized. It includes synchronization between audio and visual cues as well as between single communicative modalities such as face, head, torso and gestures. New approach should also permit to control synthesis process with the high-level easily interpretable parameters such as communicative intentions or intensity.

With the long aim of multimodal laughter synthesis in this paper we focus two aspects, namely, the modulation of the laughter visual intensity and the respiration animation. In particular, not much is known on which visual cues participate to the perception of laughter intensity. Interestingly the so-called silent laughter (i.e. when no sound is perceivable) can be perceived as highly intense [13]. Controlling the intensity of synthesized laughter is an important aspect of laughter synthesis. The intensity is a very intuitive high-level variable that can be used to control laughter synthesis and to generate laughs that are appropriate to the situation context and the communicative intentions of the laughing agent.
Respiration has also a particular role in laughter production. It is one of the most significant cues and is strongly visible. Moreover, as a physiological process, it drives the audio and visual expressive patterns and probably decides on the synchronization of different modalities.

3.1 Database and annotation

For the purpose of this work we used the AudioVisualLaughterCycle (AVLC) corpus [14] that contains about 1000 spontaneous audio-visual laughter episodes with no overlapping speech. The episodes were recorded with the participation of 24 subjects. Each subject was recorded watching a 10-minutes comedy video. Thus, it is expected that the corpus contains mainly only one type of laughter namely hilarious one. Each episode was captured with one motion capture system (either Optitrack or Zigntrack) and synchronized with the corresponding audiovisual sample. The material was manually segmented into episodes containing just one laugh. The number of laughter episodes for a subject ranges from 4 to 82.

Next, through perceptive study, human coders annotated the perceived intensity of the AVLC laughter episodes using a Likert scale from 1 (low intensity) to 5 (high intensity) (for details see [13]). Each episode was manually annotated by minimum 6 and maximum 9 coders. In the rest of the paper we use a part of this dataset: 1528 intensity annotations for 249 laugh episodes of AVLC corpus (corresponding to 6 subjects). The intensity coder's agreement, Krippendorff κ coefficient, for this part of the dataset is 0.65.

Finally in the respiration study we used the manual annotation of the respiration phases proposed by Urbain and Dutoit [15]. Each laugh episode in AVLC corpus [14] was manually annotated to indicate the airflow direction (inhalation or exhalation).

4 Laughter Intensity Modulation

In this section we propose a solution to model laughter with different intensity values. Our rational is to modify laughter production so that its intensity is perceived differently. We use a data driven approach for facial animation and we propose a method to modulate automatically the intensity of the laughter expression.

At first, we carried out a study to discover which facial cues are related to the perception of intensity level. We rely on the annotation of perceived intensity of laughter (see Section 3.1). We link the perceived intensity with facial cues. Facial cues are characterized by a set of distances between facial markers (recorded with motion capture system). They were chosen as they correspond to specific muscular activities (related to action units [16]). For each episode of the AVLC corpus we extract such distances between the facial markers. We are particularly interested in the cues that can be associated with intense laughs. Having the values of these distances, we check their correlation with perceived intensity. Then we use such results to elaborate a computational model that modulates any animation of laughter depending on its intensity level.

4.1 Facial Expression of Laughter

To define the cues that are significant in laughter expression we look at the facial actions that occur in laughter expressions. Laughter contains usually the activation of the zygomatic major muscle that corresponds to the action unit AU12. Additionally the cheek raise is often present; it corresponds to the activation of the orbicularis oculi muscle (action AU6). Its presence is associated with the Duchenne or hilarious laughter. There are other facial actions that may occur in the expression of laughter. For example mouth opening (AU25) and jaw drop (AU26) were observed quite often in the study of Beermann et al. [17]. The same study reports, albeit more rarely, the occurrence of the lid tightener action AU7 and of the lip corner depressor action AU15. In the acted expressions of hilarious laughter, the actions AU25, AU26 are frequently observed while AU7, AU27 (mouth stretch), AU4 (frown) occur less and AU1 (inner raise eyebrow), AU2 (outer raise eyebrow), AU9 (nose wrinkling) and AU20 (lip stretcher) occur occasionally [18]. On the other hand in naturally occurring laughter, actions AU5 (upper lid raiser), AU6, AU7, and AU9 are observed [8]. Apparently some of these actions may be particularly related to laughter intensity. Indeed, Darwin [19] claimed that intense laughter will include lowering of the eyebrows (AU4).

Other actions such as AU7 and AU9 are also sometimes considered to be an indicator of strong laughter.

4.2 Data Analysis

We analyzed the motion capture data of the AVLC corpus [6] which was annotated with intensity values. We introduced 12 measures (D1 - D12) that correspond roughly to the action units observed in the laughter expressions: AU6, AU4, AU7, AU12, AU25, AU26 (see Figure 1). The computed distances are normalized to the neutral expression in the motion capture data. The distances used in our study are presented in Table 1.

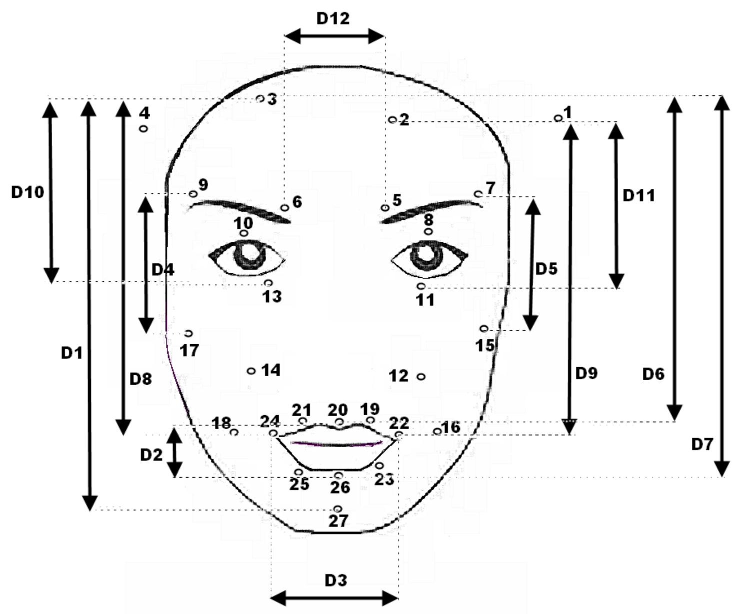

Fig. 1. Position of the markers and distances D1-D12

The measurements D4-D5 and D8-D9 correspond roughly to action units considered to be specific for the facial expression of hilarious laughter, namely cheek raising - AU6 and smile (lip corner up) - AU12. The remaining measurements correspond to the action units which may occur in certain laughs (see Section 4.1) i.e. AU4 (D12), AU25 and AU26 (D1, D2, D3, D6, D7), AU7 (D10-D11). All these distances are computed at 25 FPS.

For each laugh episode, the values D1-D12 of single frames are mapped to a fixed-length feature vector with the help of the following functions: minimum, maximum, range and mean. Since we have 12 facial distances and 4 functions, we

Table 1. Distances D1-D12

id	name	value	direction
D1	jaw movement	3-27	vertical
D2	lip height	20-26	vertical
D3	lip width	24-22	horizontal
D4	cheek raising (right)	17-9	vertical
D5	cheek raising (left)	15-7	vertical
D6	upper lip protrusion	3-20	depth
D7	lower lip protrusion	3-26	depth
D8	lip corner movement (right)	24-3	vertical
D9	lip corner movement (left)	22-2	vertical
D10	lower eyelids movement (right)	3-13	vertical
D11	lower eyelids movement (left)	2-11	vertical
D12	frown	5-6	horizontal

obtain a feature vector of 48 features per episode. We calculate the correlations between distances D1-D12 and the intensity annotations of the corresponding laugh episode (see Section 3.1). The detailed data are presented in Table 2.

Table 2. Correlation between laughter median intensity and the distance features

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
min	0.40	0.34	0.14	0.19	0.11	0.17	0.27	0.20	0.17	-0.23	-0.22	0.10
max	0.67	0.63	0.46	0.27	0.29	0.20	0.58	0.33	0.44	-0.09	-0.06	0.38
range	0.49	0.44	0.42	0.39	0.41	0.40	0.51	0.34	0.28	0.45	0.49	0.21
mean	0.63	0.61	0.42	0.25	0.25	0.19	0.52	0.31	0.42	-0.18	-0.16	0.31

The strongest correlation is observed for the maximum jaw and lip openings, i.e. the distances D1 and D2, using the "max" function computed over the whole episode ($\rho = .67$ and .63, respectively). Strong correlation is also observed for maximal lower lip protrusion (D7) ($\rho = .58$). All these three measures received comparable strong correlations when computed as a mean over the whole episodes. On the other hand, these three distances correspond to the activation of the action units AU 25 and AU 26. This might suggest that the perceived degree of intensity is correlated with the mean and maximal activation of AU 25/26 and, in other words, with the mouth opening. Relations between the perceived intensity and the other distances were less strong. In our test the correlation between the perceived intensity and the measures D4 and D5 (cheek raise) was weak ($\rho = .27$ and .29). It does not mean that this activity was not observed in the dataset. Indeed cheek raise is present in the considered episodes but its presence is not so strongly correlated with the perceived intensity. We obtained similar results for AU12. The correlation between perceived intensity and the measurements D3, D8, and D9 is only slightly higher (0.33-0.46 for maximum function, and 0.31 - 0.42 for mean function) than for the distances corresponding to AU6. Distances D10-D11 corresponding to the lower eyelids movement (AU7) are even less correlated with the perceived intensity. This result, however, might be influenced by the eyes blinking. Finally also D12 that corresponds to AU4 (frowning) is slightly correlated with the perceived intensity ($\rho = .38$).

Interestingly, the overall duration of the laugh is not strongly correlated ($\rho = .54$, see Figure 2) with the perceived intensity. In other words, an intense laugh does not necessarily last long, and vice-versa.

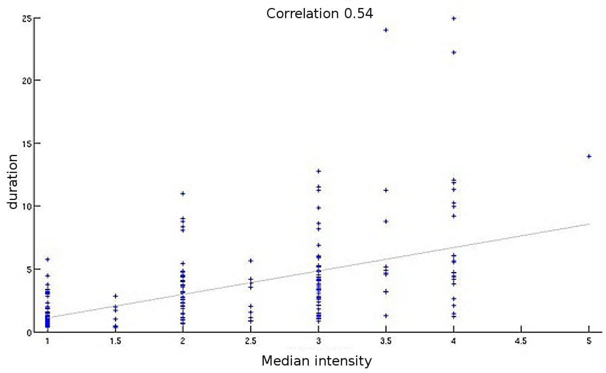

Fig. 2. Correlation between median intensity and laughter duration

These results show that only some visual features are strongly related to the perceived intensity of laughs. In other words, rather than a simple linear increase of the activation of all facial cues, intense laughter is expressed by activating some additional actions units, or by the gradual changes of single action units. This important conclusion will be used, in the next section, to synthesize laughs with the desired intensity.

4.3 Synthesis

The intensity of the facial expression is often modeled in virtual agents by using a simple linear function (such as proposed in [20]). In such approach all facial parameters of the face are multiplied by one intensity value. Thus the values of all facial parameters are proportional to the intensity value. The results of our study in Section 4.2 shows that such approach in the case of laughter expression would not be appropriate. For this reason we propose a novel approach for the modulation of the intensity of laughter animation. In our approach only facial parameters corresponding to certain actions units (AUs) are modulated while others are not. Moreover facial parameters corresponding to different facial actions are modified independently. Some of them are activated only for high intense expressions. The intensity modulation is done at the level of action units and thus it is independent from different facial animation parameterizations used to animate virtual agents. It can be applied for both procedural animation and motion capture data.

For the synthesis we use the virtual agent system that is MPEG-4 compliant. We modulate the intensity of any original expression according to the results of the analysis described in the previous section. Our intensity modulation module works as a filter that modulates any laughter animation. Figure 3 presents the pipeline. In this application we use the motion capture data from AVLC dataset. The original motion capture data is converted into Facial Animation Parameters FAPS (of MPEG-4 [21]) according to the procedure described in [6]. Next, MPEG-4 compliant animation is modulated by the intensity module described below and the final animation is displayed by the virtual agent. Additionally the original (prerecorded) audio file is synchronously played with the modified animation.

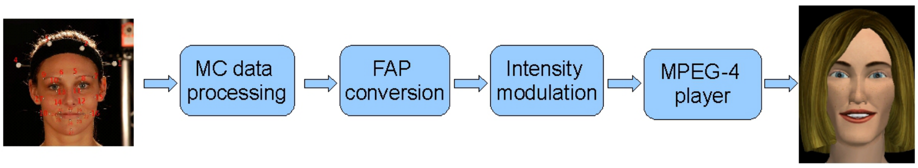

Fig. 3. Laughter intensity modulation

Our intensity module modulates the values of the facial animation parameters FAPS corresponding to AU25, AU26, AU4 and AU7 (see also Section 4.1). Values of FAPs corresponding to the actions AU25 and AU26 are modified proportionally to $\Delta(intensity)$ where $\Delta(intensity)$ is the difference between the perceived intensity of the original data and the requested intensity. The values of FAPS corresponding to AU4 and AU7 are activated only if the values of the former exceed certain activation values. The FAPS corresponding to the AU12 and AU6 are not changed. MPEG-4 does not allow for the animation of AU9.

It is important to notice that once we have the animation described in facial animation parameters the intensity modulation can be done in real-time (data retargeting from the original motion capture data to facial animation parameters is not yet real-time).

Figure 4 presents several frames of an animation generated with our approach. In the first line one can see the original animation reproduced from the motion capture data. It serves as basis of comparison with the animation modified by the intensity modulation module. The video corresponding to this animation was perceived as medium intensity laugh (median value is 3 in 5 points scale from 1 to 5). In this example we increase this laugh intensity. One can see that the facial expressions on the frames of the modified animation (second row) are characterized by a stronger mouth opening. Additionally in the column Figure 4c) the action units AU4 and AU7 are visible. Thus the final animation is not a simple linear filter applied over the whole face but facial parts are differently modulated according to the empirical result on the perception of the intensity.

a) b) c) d)

Fig. 4. Example of laughter episode with different intensities

5 Respiration

The visible respiration is an important part of expression of the laughter. A respiration cycle in laughter usually begins with an "initial forced exhalation", that is followed by a "sequence of repeated expirations" of high frequency and low amplitude. In longer laughter episodes the expiratory phases are interlaced with inhalations [8]. Interestingly the synthesis of the respiration is ignored in the virtual agent animation. During respiration, an important cue is the synchronization between modalities such as facial expressions and body movements. Indeed, facial, body and respiration cues are driven by the same physiological processes. It is shown that the two respiration phases correspond to different audiovisual patterns [13]. For example it is argued [8] that the backward tilt of the head facilitates the forced exhalations.

In this section we focus on the respiration during the laughter. First, we study the relation between the respiration phases and the facial cues. We extract some relations that characterize the synchronization mechanism across modalities in laughter. Second, from the physiological respiration data gathered through sensors, we replay the respiration animation with an MPEG-4 compliant agent.

5.1 Data analysis

We studied the relation between the visual cues and the respiration phases. For this purpose we used again the data from the AVLC corpus and the manual annotation of the respiration phases developed by Urbain and Dutoit [15]. We considered 142 laughs that contain more than one respiration phase. They contain 190 exhalation and 190 inhalation phases. We also used the same 12 measurements, namely D1-D12, and we checked if they have different values in the inhalation and exhalation phases. For each considered respiration phase, the values D1-D12 corresponding to single frames were mapped to a fixed-length feature vector using 4 functions minimum, maximum, range, mean. We used two-sample Kolmogorov-Smirnov test to check whether D1-D12 have different values within the inhalation and exhalation phases. The detailed results are presented in Table 3.

Table 3. Mean distance differences between exhalation and inhalation phases (significant values in bold)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
min	**-0,80**	**-1,20**	**-1,66**	**-0,92**	**-0,91**	**-0,29**	**-1,27**	**-1,06**	**-1,02**	**-0,27**	**-0,23**	**-0,13**
max	**0,46**	**0,45**	0,36	0,26	0,30	0,16	0,61	0,28	**0,34**	**0,18**	**0,23**	0,02
range	**1,26**	**1,65**	**2,03**	**1,18**	**1,21**	**0,44**	**1,88**	**1,35**	**1,36**	**0,45**	**0,47**	**0,16**
mean	-0,08	-0,12	-0,14	-0,06	-0,02	-0,01	-0,11	-0,06	0,01	-0,09	-0,08	-0,04

According to the obtained results the distances D1-D12 differ significantly between two respiration phases for 2 functions: range and min. The 'max' values corresponding to the mouth opening (i.e. distances D1-D2) are significantly bigger in the exhalation phase. In other words, mouth opening is more intense in this respiration phase. The maximal distances D4-D5 and D8-D9 that correspond to AU6 and AU12 are also bigger in this phase but only for D9 this difference is significant. From these results, it emerges that in one phase the mouth is more often widely opened. This hypothesis should be however confirmed using more precise respiration data.

5.2 Synthesis

To generate the respiration animation we use the data gathered with the The ProComp Infiniti system[1] which serves for biofeedback data acquisition. This system contains high accuracy respiration sensor that provides the thorax and abdomen expansion with 256 samples per second. On the other side, MPEG-4 standard does not allow us to modify the body shape; it solely permits to animate the body skeleton. To simulate respiration and corresponding chest movement we had to extend the set of body animation parameters. The body of the agent is defined by bones. To simulate the chest movement we added two additional bones at the level of the thorax. Next, the normalized data from the respiration sensor are used to animate the additional bones independently to the rest of the body. Figure 5 presents frames of the body animation corresponding to inhalation and exhalation phases.

[1] http://www.thoughttechnology.com/index.html

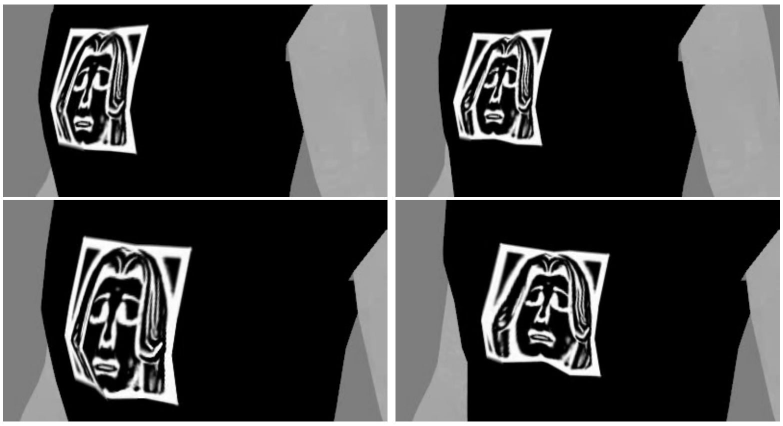

Fig. 5. Animation of two respiration phases: first column - inhalation phase, second column - exhalation phase.

6 Conclusion and future works

The laughter synthesis is a very complex task that has not been much studied before. In this paper we discussed several issues related to laughter synthesis, in particular: intensity modulation and respiration modeling. We studied the relation between visual cues of laughter and the perceived laughter intensity, as well as between the visual features and laughter inhalation and exhalation phases. We also proposed a motion capture data-driven laughter intensity model and a physiological data based respiration animation.

Several limitations of this work should be noted. First of all, so far we have worked with only two communicative modalities: face and body motion during respiration. This work is also limited to only one laughter category i.e. hilarious laughter. Concerning data, we use the motion capture dataset corresponding to only 6 human subjects. More subjects have to be considered to allow us to consider individuals as well as intra-subjects differences in expressive behaviors. Indeed there may exist different "laughing styles" that may depend for example on personality factors (e.g. extraversion) or even on physical and physiological characteristics of the laughing person (e.g. weight, lungs volume). In the intensity analysis, so far, we do not consider the dependencies between different distance measurements of facial features. Very likely, some of these measurements are interrelated, e.g. this may be the case for the measurements D8-D9 and D4-D5. Other factors such as the duration of single facial actions in the laughter expression may influence the perceived intensity and, thus, should also be analyzed.

This is an ongoing work. At the moment we are preparing an evaluation of the intensity model. The evaluation will be organized through perceptive tests where the original and intensity modulated animations, as well as videos extracted from the original AVLC dataset will be evaluated by the naive users by using the same intensity scale. Regarding the respiration modeling, we are now working on the synchronization of the respiration animation with the facial animation. For this purpose we use results of the study described in Section 5.1. Last but not least we will extend our model by introducing other modalities. First of all we plan to integrate laughter audio synthesis. The analysis of the relation between certain acoustic parameters and the perceived intensity [13] shows that this relation can be even stronger than in the case of facial cues. Thus intensity model should be able not only to modify facial animation but also corresponding sound of laughter. At the same time we will also work with different corpora to introduce arm gestures to our model.

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