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Human-humanoid robot social interaction: Laughter

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***Abstract*— In this paper, we describe a human gesture recognition system developed to make a humanoid robot understand non-verbal human social behaviors, and we present the results of preliminary experiments to demonstrate the feasibility of the proposed method. In particular, we have focused on the detection and recognition of laughter, a very peculiar human social signal. In fact, although it is a direct form of social interaction, laughter is classified as semi voluntary action, can be elicited by several different stimuli, and it is strongly associated with positive emotion and physical well-being. The possibility of recognize, and further elicit laughter, will help the humanoid robot to interact in a more natural way with humans, to build positive relationships and thus be more socially integrated in the human society.**

Keywords*— Human-robot interaction; humanoid robot; gesture recognition; sensing; bioinstrumentation

I. INTRODUCTION

ONE of the most ambitious objective of modern research in robotics is to enable robots to interact with humans at the same level of perception to naturally integrate the robot in the human society [1], [2].

To achieve this, engineers have made a great effort analyzing in deep general users casual interaction with different types of robots either within a single interaction or over a long time span [3]–[6]. Unfortunately, only few works have taken advantage of the vast medical literature on human social interaction [7]. However, we believe that a realistic human-robot social interaction should be based on an established and well-known human social model, and that a social able robot should be able to understand also human natural non-verbal social cues.

Objective of this paper is to present a simplified social model for human-humanoid robot natural interaction, to propose a method to allow a robot to recognize human gesture carrying social information, and to show and discuss the results of the preliminary experiments to validate the feasibility of the proposed method.

The structure of this paper is as follows: section II presents the human-humanoid robot social interaction model, the proposed method, the hardware system for human gesture recognition, and the experiments protocol. Section III presents the preliminary experimental results; section IV discusses the trends extrapolated from the results. Section V summarizes the contents of the presented work and gives an overlook on future developments.

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II. MATERIALS AND METHODS

Fig. 1 shows a general natural human-human social interaction cycle model, as developed by psychologists [8]. To be as natural as possible, then, human-humanoid robot interaction should be based upon this model. However, understanding and reproducing this model with a robot is very difficult, because its analysis is based on notions of cognitive psychology that are not quantifiable.

At a glance, in fact, human social interactions with other humans or, more in general, with other creatures are quite complex and can be affected by several factors. In particular, reactions deriving from the cognitive, emotional, and physiological status of the subjects are variable and hardly predictable in a specific social situation [7], [9]. To perform a completely natural interaction, socially able robots should take into account all these factors, but this task is nearly impossible without an extensive previous knowledge of the

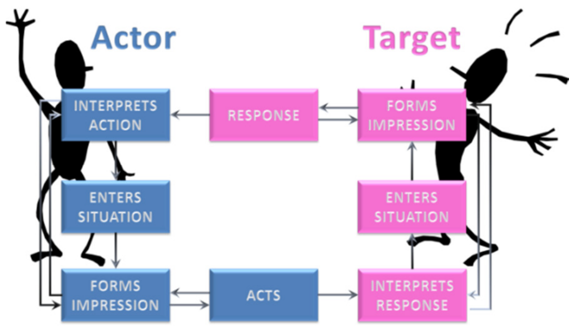

Figure 1. The general social interaction cycle

partner. The previous considerations on the complexity of the phenomena are important but we need then to simplify the problem to be approachable.

To create a general model we cannot make any preliminary assumption on the target human, the only observable entity is his behavior and the consequent response. Therefore, we adopted a behaviorist point of view: a behavior can be explained without considering mental states or consciousness, but as a direct reaction to a particular stimulus [10], [11]. Bypassing the unknown steps in the cycle, the robot should now be able to map each stimulus to its corresponding human response and the robot could be able to induce a specific behavior with a specific action. Therefore, we eliminated the correspondent interactions among the blocks and developed a cyclical model for human-humanoid robot interaction, as shown in Fig. 2. In this model, the only part we can control is the one related to the robot.

The first step to validate this model is demonstrating that the robot is able to recognize human non-verbal social action and corresponding behavior. In this paper, we focused on validating the behavior recognition ability of the robot.

Studies on how instinctive and unconscious responses to involuntary physical signals affect human social communication already exist, and generally related to neuroscience [9].Unfortunately, though, very few of these studies are supported by objective measurement data, transferable to robotics. Among all these instinctive social acts typical of the human species [9], one of the most interesting is laughter [12]. This is supported by the fact that, in the last decades, studies on laughter have been intensified, as many researchers in different fields have tried to identify and isolate the relationships between laughter, sociality and physical well-being [13]–[17]. Laughter, in fact, has some quite peculiar characteristics: it can be elicited by several different stimuli; it is both a direct form of social interaction and a semi-conscious reflex, it is associated with positive emotion and physical well-being, and especially, it can be objectively measured monitoring physical and physiological parameters [12], [17]–[23].

A robot able to recognize and elicit laughter might have quite a good range of applications, not only in the entertainment, but also in the healthcare field [13]–[16], we chose laughter as human benchmark behavior to validate our model.

Even if laughter can be easily recognized by fellow humans, its characteristics are highly variable not only among individuals, but also considering the same subject. Therefore, we decided then to run preliminary experiments to verify if laughter can be easily measured and differentiated from other behaviors with an objective measurement system, possibly using non-invasive sensors.

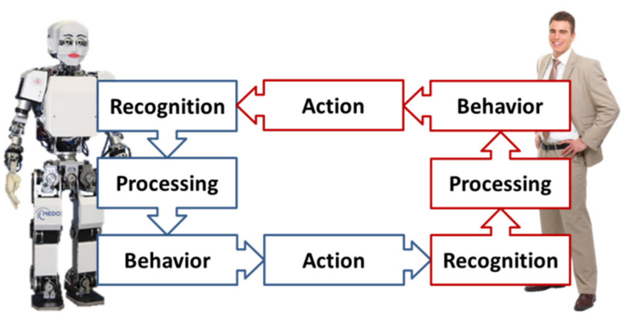

Figure 2. human-humanoid robot social interaction cycle

A. Human movement measurement system

In order to analyze the subject's behavior in real-time, we needed a system to measure both the subject's movements and physiological parameters, independent from the surrounding environment and not interfering with the subject's freedom of movement. Although laughter has unique audio characteristics, which have been already quite extensively analyzed [22], it is somehow difficult to separate laughter of specific target individuals in a laughing group.

Moreover, even if the highly stereotyped movements associated with laughter can be easily detected with a camera, their quality and intensity are nearly impossible to be objectively measured and accurately classified based solely on a video recognition algorithm [24].

We decided then to use a system composed by a set of IMUs (Inertial Measurement Units) named WB-4 (Waseda Bioinstrumentation system No 4) to measure the movements associated with laughter of the target subject, paired with a Bagnoli™ Desktop EMG (ElectroMyoGraphy) set, to measure the physiological activation of the muscles during these movements.

The WB-4 IMU is very compact and lightweight (Fig. 3) [25], and due to its extremely reduced dimensions and the absence of wired connection WB-4 is a suitable device for our application compared to all the other various traditional measurement systems [26].

B. Waseda Emotional Robot KOBIAN

To elicit laughter on the subject we used one of the robots developed at Takanishi laboratory is the Emotion Expression Biped Humanoid Robot KOBIAN (Fig. 4). This humanoid has a total of 65-DoFs and several different sensors to interact with the environment and its human partners [27].

Its size is similar to the average Japanese adult female and its total weight is 62kg. We decided to use the KOBIAN for these experiments on laughter for several reasons. First of all, we already have from several past studies a good idea on how general users perceive this robot [28]. In addition, this version has improved the design of the head, equipped with 24-DoFs, to perform various dynamic facial expressions, even asymmetric ones (Fig. 5), and past experiments demonstrated

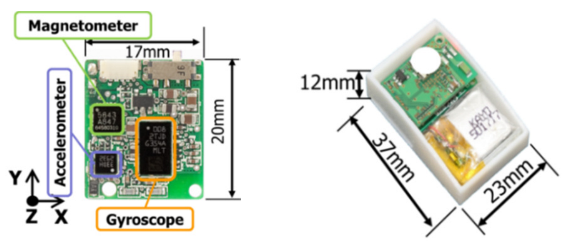

Figure 3. WB-4 IMU (left); Wireless IMU with housing (right).

that these expressions are easily recognized by subjects [29]. Furthermore, the robot appearance is definitely robot-like makes it more suitable to avoid falling in the uncanny valley when evaluating subjects' reactions in a human-robot interaction experiment [30].

C. *Method*

Running experiments to measure social responses is always very difficult. As stated before, environmental conditions actively modify the inner state of subjects, so the risk of collecting altered data is very high.

Even the simple interaction with the real robot can induce stress in subjects not familiar with it, again influencing the results of the experiment. For this reason, and since we are focusing only on the objective recognition of the human behavior, which should be as natural as possible, the experiments were run outside the laboratory environment, in a casual room, using instead of the robot itself recorded videos of the robot, embedded within other videos of well-known comedians, to make the subjects be at ease and help build up their humorous state.

D. *Experimental protocol*

The preliminary experiments were carried out with five healthy volunteers, average age of 23 (21-24 years old), with no invasive devices and without any risk for the health of the participants. The right to privacy of the subjects has been fully respected, the subjects have been extensively informed and asked for the consent to the experiment, also taking into account their age and their health conditions, according to the existing national and international laws and regulations.

Two synchronized WB-4 IMUs acquired data at a sample rate of 200Hz and were connected via Bluetooth with a standard personal computer for continuous data logging.

Three synchronized EMG devices acquired data at 1kHz, and were connected via a Bagnoli™ Desktop EMG System with another standard personal computer for continuous data logging.

The two WB-4 IMUs and two EMG sensors were fastened with tight bandages on the umbilical region, and on the xiphoid process, to measure both the movement and the physiological activation of the rectus abdominis, and the diaphragm, respectively (Fig. 6). The third EMG sensor was fastened on the right side of the rib chest, on the intercostal space between the 8th and the 9th ribs, to measure the activation of the intercostal muscles.

A digital high resolution video camera (1440 x 1080 @ 30 frames/s) recorded the experiments. The video camera was centered on the subjects' face to clearly identify the laughing events.

Subjects sat comfortably and watched experimental videos on a wide screen TV set for about 10 minutes.

Experimental videos were continuous, and divided in three sections of about 3 minutes each: an initial and final section showing a popular comic show with well-known comedians performing comic acts, and a central section showing videos of the KOBIAN robot performing a series of comic actions mimicking performances of well-known comedians. Before the video session, subjects were asked to forcedly laugh for 5s to provide data for forced (unnatural) laughing, and then they were actively tickled for 5s to assess their capability of natural laughing under the experimental conditions as well as to provide the sensors system a randomized movement control set of data.

Data analysis was run offline, separately for each sensor, to verify which sensor is more useful and which position is the most significant to recognize laughter. All the recorded videos of the subjects and the data streams were manually segmented and compared, and categorized in four categories, to be used as the training data sets:

- Tickling
- Fake laughter
- Laughter
- No action

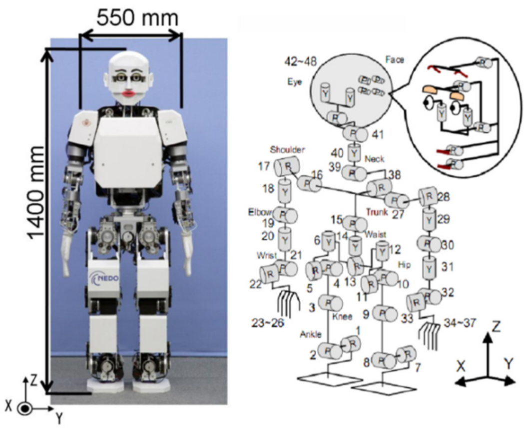

Figure 4. KOBIAN

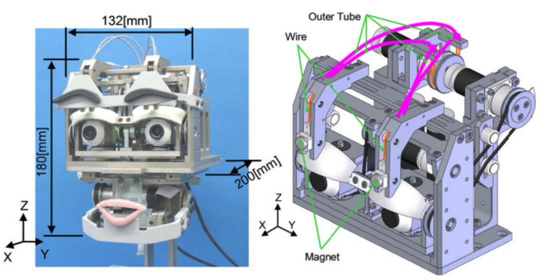

Figure 5. KOBIAN head

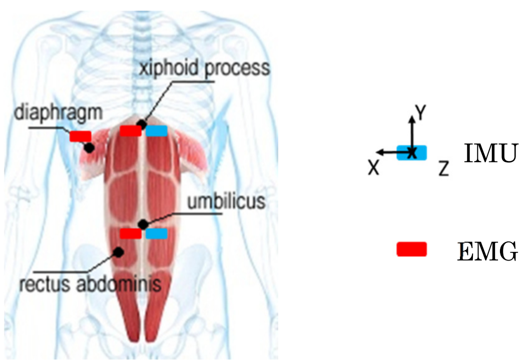

Figure 6. sensor positioning

III. Results

A. IMU: Laughter movement analysis

We divided each data set in non-overlapping rectangular windows of the same length and we extracted several features to be used for discrimination between different data sets. We performed the same analysis using five different data window lengths, 10ms, 20ms, 50ms, 70ms, and 100ms, and compared the results. The data collected with the IMUs were:

- Acceleration X-Y-Z
- Acceleration norm (calculated from X-Y-Z data)

For each data stream, the features taken in consideration for the analysis were:

- Acceleration maximum
- Acceleration minimum
- Zero crossing rate
- Short time energy
- Standard deviation

in the time domain, and

- Peak
- Minimum
- Spectral roll-off
- Spectral centroid
- Spectral flux

in the frequency domain.

These features are commonly used in digital signal processing, especially for musical and speech recognition applications, to characterize signals [31], [32].

In particular, in the frequency domain, we determined the features based on the FFT of the windowed signal. The Spectral Roll-off SR is defined as the frequency boundary below which the C% –in our case 90%– of the total power spectrum energy resides:

$$\sum_{n=1}^{SR} S(n) = C \sum_{n=1}^{N} S(n) \qquad (1)$$

This measure is useful in distinguishing highly transient signals, which have high proportion of energy contained in the high-frequency range of the spectrum, from more constant signals where most of the energy is contained in lower bands.

The spectral centroid is calculated as the weighted mean of the frequencies present in the signal:

$$\text{Spectral Centroid} = \frac{\sum_{n=1}^{N} nF(n)}{\sum_{n=1}^{N} F(n)} \qquad (2)$$

The spectral centroid indicates the center of gravity of the spectrum, and more generally, it is a measure of central tendency used in digital signal processing.

The spectral flux is defined as the energy difference between consecutive frames. So for a frame k:

$$\text{Spectral Flux}_k = \sum_{n=1}^{N} (S_k(n) - S_{k-1}(n)) \qquad (3)$$

Where Sk(n) are the values of the current frame spectrum and Sk-1(n) the values of the last frame spectrum.

The features were all normalized in range with respect to their respective maximum and minimum value obtained during all the set of experiments. The movement discriminant analysis has been performed on the basis of Principal Component Analysis (PCA) [33]. We used the Leave-One-Out Cross Validation (LOOCV) technique to validate the results of the PCA [34].

The best results are obtained windowing data at 70 ms and are shown in Fig. 7 and Table I: movement discrimination is possible for the umbilical IMU data based on the first 5 PCs (Principal Components), with a correct discrimination rate of around 83% in the best case, with the chosen windowing. For the xiphoidal IMU data, instead, discrimination is possible based on the first 4 PCs, with a correct discrimination rate of around 75%. From the weighted arithmetic mean of the original data features over the significant PCs, we could see that the dominant factors for the PCA are the acceleration maximum, minimum and frequency peak of both the Y and Z components.

Excluding the acceleration maximum and minimum values, which can sensibly change depending on the subject and the intensity of the laughter, more stable dominant factors for the PCA are the frequency peaks for both the Y and Z components of the acceleration, as well as the short-time energy of the Y and the norm components.

B. EMG: laughter muscular activation analysis

We run a similar analysis for the EMG sensors. We divided each data set in non-overlapping windows of the same length and we extracted several features to be used for discrimination between different data sets.

For each EMG channel data stream, the features taken in consideration for the analysis were:

- RMS (Root Mean Square) not normalized
- STD (STandard Deviation)

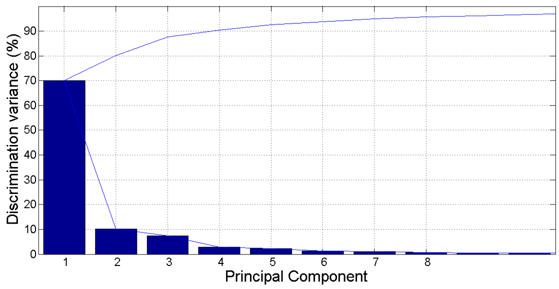

Figure 7. Umbilical IMU PC contribution rate

TABLE I
UMBILICAL IMU PCA LOOCV RESULTS

	10ms	*20ms*	*50ms*	*70ms*	*100ms*
PC base	7	4	4	5	4
Correct rate	0.7234	0.7139	0.7552	0.838	0.8121
Total data windows	104757	52376	20951	14924	10473
Unrecognized Laughter samples	8267	5189	2176	1477	995
Unrecognized Fake Laughter samples	2007	1008	334	230	179
Unrecognized NoReaction samples	18502	8623	2599	682	779
Unrecognized Tickle samples	199	163	19	28	15

- Mean
- Integrated signal
- Peak

in the time domain, and:

- Mean
- Median
- SMR (Signal-to-Motion artifact Ratio)
- Power
- Bandwidth

in the spectral domain.

Since the EMG sensors sampling frequency is five times higher than the IMU sampling frequency, we used wider windowing steps. We performed the same analysis using five different data window lengths, 100ms, 200ms, 500ms, 700ms, and 1000ms, and compared the results.

The intercostal EMG signal was completely covered by the heartbeat signal; consequently we discarded this sensor data, and carried out the analysis only on the umbilical and xiphoidal EMG data.

The features were all normalized in range with respect to their respective maximum and minimum value obtained during all the set of experiments. For the EMG data as well, the movement discriminant analysis has been performed on the basis of Principal Component Analysis (PCA). Again, we used the Leave-One-Out Cross Validation (LOOCV) technique to validate the results of the PCA.

This time, the best results are obtained windowing data at 1000ms and are shown in Fig. 8 and Table II: movement discrimination is possible for the umbilical EMG data based on the first 3 Principal Components (PC), with a correct discrimination rate of 74%, and for the xiphoidal EMG data based on the first 3 PC, with a correct discrimination rate of

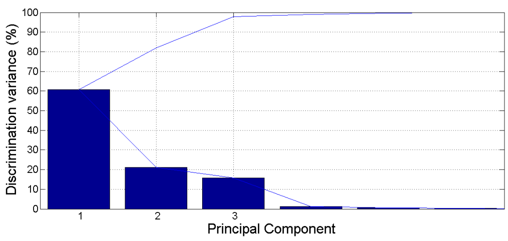

Figure 8. Umbilical EMG PC contribution rate

TABLE II
UMBILICAL EMG PCA LOOCV RESULTS

	100ms	*200ms*	*500ms*	*700ms*	*1000ms*
PC base	6	4	3	3	3
Correct rate	0.7124	0.7178	0.7301	0.7345	0.7408
Total data windows	43797	24890	9286	7223	5119
Unrecognized Laughter samples	7651	3240	1290	918	761
Unrecognized Fake Laughter samples	746	481	97	74	17
Unrecognized NoReaction samples	3999	3124	1056	869	520
Unrecognized Tickle samples	201	179	64	57	29

70%. From the weighted arithmetic mean of the original data features over the significant PCs, we could see that the dominant factors for the PCA are the RMS, mean and peak signals. Excluding the mean and peak values, which can sensibly change depending on the subject body and the intensity of the laughter, more stable dominant factors for the PCA are the frequency bandwidth and median.

IV. DISCUSSION

The results obtained by these experiments, albeit preliminary, clearly show that laughter is objectively measurable and recognizable with non-invasive sensors, such IMUs and superficial EMG. In fact, the obtained results show that this system can recognize real laughter with a correct discrimination rate of at least 74%. In addition, from the analysis of both the sensors and camera data, several bouts of laughter that would have been undetected, or mistaken for simple smiling, with only the camera, were clearly detected and classified as laughter by both the IMU and EMG sensors.

Another important point to highlight is that in the medical practice, the EMG measurement of diaphragm activation for respiration is best taken on the xiphoidal process. Being laughter performed by modulating the respiration, using the same measurement protocol seems natural. Instead, for laughter measurement purposes, the measurement of the rectus abdominus muscle activation is more effective than the measurement of the diaphragm muscle activation.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we addressed the problem of human-humanoid robot social interaction. Integrating a robot in the human society is not straightforward, because the robot must be able to understand all the voluntary and involuntary human partners' social cues and adapt its behavior consequently. Based on a human social interaction model widely used in psychology, we developed a simplified human-humanoid robot social interaction model. We then proceeded to demonstrate the possibility for a robot to recognize human non-verbal social actions.

We described an IMU and EMG based human gesture recognition system. With this system, a robot will be able to recognize at least one human non-verbal social action, namely laughter, thus validating the recognition module of our social model. The results obtained by the preliminary experiments clearly show that laughter is objectively measurable and recognizable with our system.

In the future, we plan to refine the whole developed system following different strategies. First, we will try to find the best measurement position on the human body, to increase the individual performance of the sensors, thus reducing the number of necessary sensors in the system. We must then design a wearable interface to obtain a more natural method to measure laughter, applicable also to spontaneous casual interaction situations.

Second, we will explore more characteristics that can be used to better discriminate various types of laughter, and we will run an overall discrimination analysis combining all the most important data of all the sensors. Also, we must collect a much wider number of different laughter and casual human body movements, in order for our laughter recognition system to be more robust and reliable.

At last, the whole analysis has been conducted offline, for each individual sensor, thus protracting the classification computation well out of realistic real-time classification timings. Once the best sensor position and the most significant parameters have been isolated, we have to improve the algorithm for real-time classification. In fact, this laughter classification system, although it may be used for standalone applications, has been originally developed to enhance the human behavior recognition abilities of a humanoid robot. So we will need to upgrade the recognition module to recognize laughter in real-time, mount it on the robot, and run live human-robot interaction experiments.

The final target of this project is validating our human-humanoid robot social interaction model. The following obvious step in this direction will be to study all the possible methods to elicit laughter, and isolate the most suitable ones to be used by the robot in various interaction situations; and then move on to recognizing other different types of non-verbal social actions.

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