Affective Handshake with a Humanoid Robot: How do Participants Perceive and Combine its Facial and Haptic Expressions?

M.Y. Tsalamlal, J-C. Martin, and M. Ammi
University of Paris-Sud/ LMISI-CNRS
Orsay, France
lastname@limsi.fr

A.Tapus
ENSTA Paris-TECH
Saclay, France
adriana.tapus@ensta-paristech.fr

M-A. Amorim
University of Paris-Sud/ UFR STAPS
Orsay, France
michel-ange.amorim@u-psud.fr

***Abstract*—This study presents an experiment highlighting how participants combine facial expressions and haptic feedback to perceive emotions when interacting with an expressive humanoid robot. Participants were asked to interact with the humanoid robot through a handshake behavior while looking at its facial expressions. Experimental data were examined within the information integration theory framework. Results revealed that participants combined Facial and Haptic cues additively to evaluate the Valence, Arousal, and Dominance dimensions. The relative importance of each modality was different across the emotional dimensions. Participants gave more importance to facial expressions when evaluating Valence. They gave more importance to haptic feedback when evaluating Arousal and Dominance.**

Keywords—handshake; facial expression; emotion; human-robot interaction

I. INTRODUCTION

Today, robots must be able to interact with humans and exhibit social interaction skills [1] [2]. Such skills are required to perform specific tasks involving the collaboration with human operators (e.g., collaborative assembly) [3]. One of the major social skills is the ability to communicate emotions. Communication of emotions is clearly nonverbal. People can express and recognize emotions through a variety of nonverbal channels. These channels of communication can be used individually or simultaneously to communicate different emotional messages [4]. For instance, people use facial expressions to communicate distinct emotions, namely: anger, disgust, fear, happiness, and sadness [5][6]. Other researchers have shown that some emotions can also be conveyed through other channels. For example, anger and sadness are effectively conveyed through body posture [7]. Voice provides another effective manner to convey some cues related to Arousal, Valence, and some specific emotions [8]. Surprisingly, the haptic channel was less investigated for social and emotional communications. Recent researches have shown that similar to facial expression, gesture, and voice, the haptic channel can be used to communicate different emotions [9]–[12]. Furthermore, some works have shown that skin contains receptors that directly generate hedonic values [13][14]. One of the most frequent interpersonal interactions involving touch is probably the handshake. Handshakes are a well-known mechanism for greeting, agreements, and farewells in many cultures [4][15]. In the context of human-robot interaction, handshaking is a simple, but a significant step for robots to get closer to human partners. Therefore, handshaking is a good start point to study the human-robot touch interaction.

The current study investigates how people perceive emotions during human-robot handshake interaction. We used the Meka humanoid robot (see Figure 1.a [16]) to generate both haptic expressions, with different force features for the handshake (i.e., grasping force of the hand and the joint stiffness of the arm), and facial expressions presenting different emotions with the lips display. Participants were asked to evaluate the emotions corresponding to unimodal (facial or haptic) stimuli and to bimodal (facial combined with haptic) stimuli. The study used the three dimensional space called PAD to assess the elicited emotions [17],[18]. This space describes the emotions using three uncorrelated and continuous dimensions: Pleasure, Arousal, and Dominance. This paper focuses on modeling the mechanisms that underlie the combination of facial expressions and handshake information in the perception of each of the three emotional dimensions. Such models will enable the design of effective algorithms for the recognition and rendering of multimodal emotional cues. To model this combination process, we used a new analysis approach performed on the functional measurements within a framework called Information Integration Theory (IIT) [19]. This theory was proposed by Norman H. Anderson [20] to describe and model how a person evaluates and integrates information from a number of sources to make an overall judgment. According to IIT, the integration model of facial expression and haptic feedback can be built using a class of algebraic rules.

This paper is structured as follows. Section II highlights the major researches related to the study of emotional communication with haptic devices. Section III presents the experimental setup. Section IV presents and discusses the experimental results. Finally, Section V concludes the study and highlights future research directions.

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II. RELATED WORK

A. Communication of Emotion Via Haptic Feedback

The importance of touch in affective communication has been clearly demonstrated [15]. Recently, several studies have investigated social and affective interactions with robots or virtual agents using haptic feedback [21]. These studies concern tactile, kinesthetic, and thermal stimulations. In the current study, we address the affective perception during handshakes. Therefore, we particularly emphasize research addressing kinesthetic or force feedback interactions.

Bailenson.et al.,[22] used a relatively basic device (i.e., 2 DoF joysticks) to explore the expression of emotion through haptic feedback. They showed that people express and recognize specific emotions using different patterns of haptic behavior. Gaffary et al., investigated the recognition rate of emotions displayed by a virtual agent using facial expressions and touch [23]. The results showed that emotions with positive Valence (e.g., happiness) were better recognized with the visual modality. Emotions with a high Arousal (e.g., rage) were better recognized with the haptic modality. However, the authors observed that multimodal stimuli did not improve recognition when the emotion was already well recognized using only one of the two modalities. Based on human-animal interaction studies, Yohanan and Maclean [41] developed the Haptic Creature. It consists of a robot that mimics a small pet interacting with users through touch. Using this touch centric social robot, the authors studied gestures that participants would likely use when conveying different emotions. An experiment was conducted to study the physical features of the touch interaction. Results showed common points of contact as well as duration and intensity of gestures displayed by participants. Bickmore et al., [6] designed a virtual agent capable of physically touching users in synchrony with other nonverbal channels of communication. The agent is composed of an animated human like face displayed on a monitor fixed on the top of a human mannequin. Touch behaviors are conveyed by an air bladder that squeezes a user's hand. The authors showed that when touch is used in the context of an empathic and comforting interaction, it can lead to better perceptions of relationship with the agent.

B. Human-Robot Handshaking Interaction

In the field of Human-Robot Interaction, several works were especially interested in the design of devices and control algorithms that generate human-like handshake interactions. For example, Avraham et al., [24] developed a Turing-like handshake test to determine if a machine can produce movements similar of those generated by a human. The test is administered through a tele-robotic system in which a participant holds a robotic stylus and interacts with artificial and real partners. Different models to generate artificial handshakes were experimented, and participants were asked to identify the human-like behavior. Similarly, Giannopoulos et al., [25] presented a method to evaluate a haptic device which simulates human handshakes. The authors provided an overview of the haptic device and the control algorithm used for delivering realistic handshakes via a metal rod. Then, they compared the robot handshakes with handshakes operated by a human via the same metal rod. A subjective study revealed that the proposed algorithm was evaluated significantly more human-like than the basic algorithm. Zeng et al., [26] proposed a hybrid deliberate/reactive model to achieve natural handshaking between a human and a robot. The model was based on time/frequency based trajectory control. An experimental study showed that this control method is able to improve the handshaking performance.

As shown in this section, multiple platforms have been designed and studied in order to support emotional and social interactions trough haptic feedback. Moreover, several work investigated the design of realistic human-robot handshake for social interactions. However, the role of haptic features of the handshake to convey affective messages remains to be addressed. Equally important will be the investigation of the integration process of haptic and visual information during the human-robot affective interaction.

III. METHOD

A. Objectives

In a first paper we have discussed how unimodal facial expressions and haptic feedback stimuli were perceived, then, we examined the influence of the haptic feedback on the perception of PAD dimensions. The results showed that introducing high values for grasping force and stiffness of movement leads, to the increase of the perceived arousal and dominance compared to the visual-only condition. The main objective of this paper is to investigate how participants combined handshake and facial expression to evaluate emotional dimensions. The study is model driven at the aim of proposing a functional model of emotional multichannel integration. The model is investigated using Information Integration Theory.

B. Robotic platform

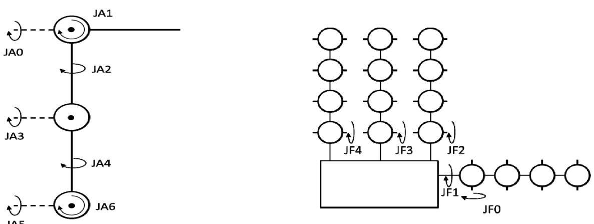
The experimental platform consisted on the Meka robot (See Figure 1). Meka is a humanoid robot designed to interact safely with human operators. The robot can display facial expressions through LED lips display and eye orientations. In this study, we focused on the lip display.

(a) (b)

Fig. 1. The Meka Robot: (a) general view of Meka platform. (b) a handshake interaction between Meka and a participant.

The handshake involves the arm, and hand of the robot. The arm has 7 DOF Series Elastic Actuators. The robot's arm is composed of seven DOF (see Figure 2): JA0 (Shoulder roll), JA1 (Shoulder pitch), JA2 (Biceps), JA3 (Elbow), JA4 (Wrist roll), JA5 (Wrist pitch), JA6 (Wrist yaw). The hand consists of a 5 DOF anthropomorphic hand. It includes of three fingers and a thumb. The three fingers are driven by a tendon [JF2-

JF3-JF4] which controls their closures. The thumb is driven by a tendon [JF0] (thumb closure) and a motor (thumb orientation) [JF1].



(a) (b)

Fig. 2. DOF of the robot's arm (a) and hand (b).

Fig. 3. Facial expressions presented to participants: Sadness (left), Neutral (middle) and Joy (right).

C. *Stimuli and conditions studied*

In this paper we focued on the bimodal condition. The studied stimuli were as follow:

- Facial Expression (FE): Facial stimuli consisted of LED lips display (See Figure 3). The expression and recognition of emotions from facial expressions has been widely studied in psychology. Observing facial muscle movements, Ekman proposed a set of criteria for classifying a basic emotions emotions [27]. Recently, researchers have shown that eyebrow and mouth are regions that carry the best information about global facial configurations [28]. Based on these works, three lip display representing three different facial expressions were presented to participants. Namely: Sadness ($\Phi FE_{Sadness}$), Neutral ($\Phi FE_{Neutral}$), and Joy (ΦFE_{Joy}).

- Haptic Feedback (HF): Haptic stimuli consisted on two haptic effects of the robot during the handshake (See Figure 1.b): the stiffness of the arm's joints, and the grasping force hand. Two types of haptic stimuli were studied. First, the high intensity haptic stimulus (ΦHF_{HI}). It combines high joint stiffness and high grasping force. Second, the low intensity haptic stimulus (ΦHF_{LO}). It combines low joint stiffness and low grasping force. The two stiffness levels corresponded to the sets of torque values assigned to each joint [JA0, JA1, JA2, JA3, JA4, JA5, JA6]. The torque values for ΦHF_{HI} were [20, 20, 20, 20, 4, 4, 4] *Nm*, and for ΦHF_{LO} were [3, 3, 3, 3, 0.6, 0.6, 0.6] *Nm*. The angles of the seven arm' joints were set to the same value for both low and high stiffness. To generate the two levels of grasping forces, two sets of angle values were assigned to the hand joints [JF0, JF2, JF3, JF4]. The angles were set as follows: wide angles [30, 300, 300, 300, 300] *deg* for ΦHF_{HI}, and small angles [30, 160, 165, 210, 240] *deg* for ΦHF_{LO}. Here JF0 was fixed. The speed of the grasping hand is fixed at 80 deg/second and the stiffness of each tendon were set to [0.1, 0.15, 0.15, 0.15, 0.15] *Nm* for both low and high intensity grasping forces.

To perform the haptic feedback during the handshake 5 steps were implemented as follows:

- Step 1: It consists on the initial configuration where the arm is relaxed and the fingers of the hand are open.
- Step 2: It consists to move the arm of the robot to the handshake initial position: the arm is outstretched and the fingers open.
- Step 3: The robot's hand closes when the subject grasps it.
- Step 4: The participant performs the handshake. The haptic feedback is displayed during 5 seconds (control parameters are presented above).
- Step 5: The hand of the robot opens after 5 seconds. The participant removes his/her hand.

Facial expression and haptic feedback stimuli were presented simultaneously during 5 seconds. The combination of facial stimuli (3 expressions) and haptic stimuli (2 feedbacks) provides six configurations. For example, it combined ΦFE_{Joy} with ΦHF_{HI} to obtain $\Phi FE_{Joy}\_HF_{HI}$.

D. *Measures*

The subjective evaluation of the three emotional dimensions (namely Pleasure (P), Arousal (A), Dominace (D)) is measured using the Self-Assessment Manikin (SAM). Particpints reported their rating using pictorial scale. This scale allows a direct rating of Arousal, Valence, and Dominance [29]. SAM is supposed to be an equal-interval scale and is equivalent to the Semantic Differential scale devised by Mehrabian and Russell [17].

E. *Participants*

21 participants (15 males and 6 females aged between 23 and 57 years old) took part in this experiment. 18 participants were right-handed and 3 participants were left-handed. The participants had no known neurological or physical injury that could affect their haptic and visual perceptions. Prior to the

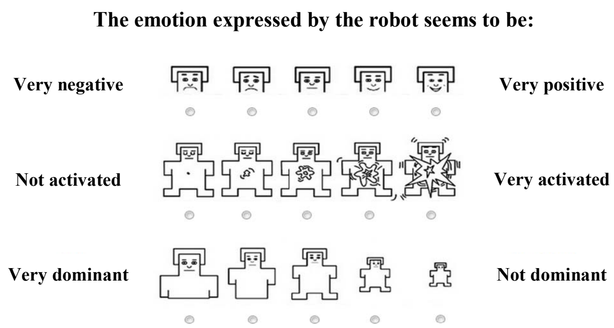


Fig. 4. Self-Assessment Manikin scale to report PAD dimensions

experimental session, participants gave informed consent. This study was approved by an institutional internal review board (IRB) of the laboratory.

F. Hypotheses

In this study, we examined how participants combine facial expression and handshake to evaluate the three emotional dimensions. We highlighted the relative effect of each modality on this evaluation. To study the combination process of the facial and haptic modality, we focused on bimodal stimuli. Based on related works, we considered the following hypotheses:

H1: Participants base their judgment on both modalities to evaluate each of the three emotional dimensions.

H2: Participants give higher importance to facial expression when evaluating the Valence dimension.

H3: Participants give higher importance to the haptic feedback when evaluating the Arousal and the Dominance dimensions.

G. Protocol

Before starting the experiment, a training session was performed to introduce the robotic platform to the participant and make sure he/she understood the course of the experiment. The participant was instructed to stay in front of the robot. In order to limit bias, the height of the robot was adjusted to the same height of the participant. During the main experiment, the participant performed three blocks of condisons: unimodal conditions blocks (i.e., facial-only and haptic-only) and a bimodal condition block (i.e., facial-haptic). All participants have been performing 38 interactions with the robot it consisted in: (4 haptic conditions + 3 facial conditions + 12 bimodal conditions) * 2 repetitions. The blocks of unimodal conditions (facial-only and haptic-only) were performed first and presented in a random order. In this paper, we focused on the combination process. Therefore, we have only examined bimodal stimuli. See [41] for unimodal analyses. whin the blocks, the stimuli were in a random order. The stimuli have 5 seconds duration. Participants were instructed to stare at therobot's head. After each interaction, the participant evaluated the perceived emotions transmitted by the robot behavior using an electronic version of the SAM scale (See Figure 4) containing a 5-points bipolar Likert scale.

IV. Results and Discussion

- **Statistical analyses**

To highlight on the effect of the facial expression and haptic stimuli, we performed a two-way repeated-measures ANOVA on participants' ratings of each emotional dimension with two within-subjects factors considered for the analysis: HF with 2 categories (ΦHF_{HI}, ΦHF_{LO}), and FE with 3 levels ($\Phi FE_{Sadness}$, $\Phi FE_{Neutral}$ and ΦFE_{Joy}). The significance threshold was set to $p < 0.05$.

Valence: Results showed a significant main effect of HF [$F(1,20) = 18.62$, $p<0.0001$] and FE [$F(2,40) = 92.17$, $p<0.0001$]. However, the interaction between the two factors was not statistically significant [$F(2, 40) = 0.3$, p = n.s].

Arousal: Results showed a significant main effect of HF [$F(1,20) = 27.95$, $p<0.0001$] and FE [$F(2,40) = 4.44$, $p = 0.018$]. However, the interaction between the two factors was not statistically significant [$F(2,42) = 2.95$, p = n.s].

Dominance: Results showed a significant main effect of HF [$F(1,20) = 135.21$, $p<0.0001$] and FE [$F(2,40) = 5.94$, $p = 0.005$]. However, the interaction between the two factors was not statistically significant [$F(2,40) = 0.47$, p = n.s].

Figure 6 illustrates participants' responses as a function of the physical scale of both emotion behaviors: Facial Expression ($\Phi FE_{Sadness}$, $\Phi FE_{Neutral}$ and ΦFE_{Joy}) and haptic feedback (ΦHF_{HI} and ΦHF_{LI}). As a first conclusion, all participants used FE and HF information to estimate each of the three emotional dimensions. We consider that **H1** was validated. The next section presents functional measurement analyses to access participants' cognitive process and highlight how they combined the haptic and visual stimuli to evaluate each of the three emotional dimensions.

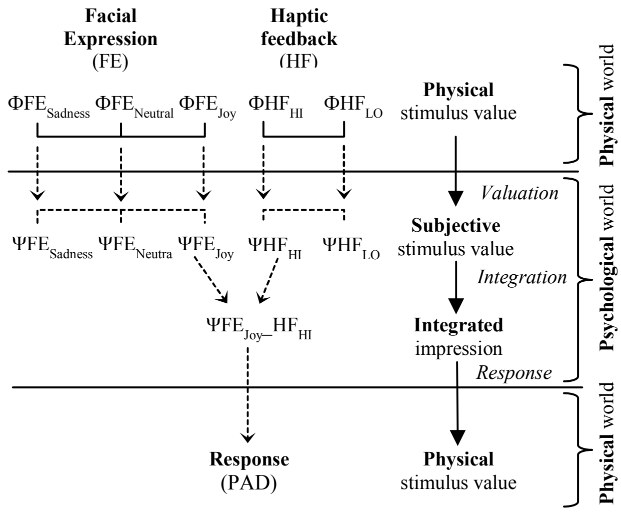


Fig. 5. Ilustration of the Information Integration Theory (IIT) framework: from stimulus presentation to participants' response.

- **Functional measurement**

Classical statistics examined participants' responses as a function of controlled variables, corresponding in this study to visual and haptic variables in the physical world (FE and HF). In contrast, functional measurement permits to access to participants' cognitive process and then to model their bimodal emotional integration mechanisms. Functional measurement (FM) proposed within the Information Integration Theory (IIT) is an approach that has been already applied to model the emotional information integration using participants internal (subjective) scaling of the physical stimuli [30]–[33]. The theory builds on three functions, corresponding to Valuation, Integration, and Action (response production) processes. The **Valuation** function corresponds to the transformation of the physical stimulus value (e.g., ΦHF_{HI}) into a subjective value (here ΨHF_{HI}) mapped on the response scale (here from 1 to 5). This cognitive process is influenced by the personal experience, external environment and task goal. This valuation is operated separately for each information source.

The **Integration** function is then used to combine the different subjective values into an internal response as illustrated in Figure 5. For example, ΨHF_{HI} and ΨFE_{Joy} combined into $\Psi HF_{HI}\_FE_{Joy}$. A class of algebraic rules (cognitive algebra) is used to model the integration process: adding, multiplying, averaging (with equal or differential weighting), etc.

Finally, the internal integrated impression is translated by the **Response** function into an observable response in the physical world. Functional measurement plots (as in Figure 7) illustrate the functional data of participants' responses expressed as a function of their subjective scaling $\Psi FE_{Sadness}$, $\Psi FE_{Neutral}$ and ΨFE_{Joy}, corresponding to each physical stimulus value $\Phi FE_{Sadness}$, $\Phi FE_{Neutral}$ and ΦFE_{Joy} of FE. Subjective values (Ψ) are approximated by the marginal means of responses given by participants for each physical FE condition, (for example, as shown in the abscissas of Figure 7). For example, participants' estimation of Dominance for $\Phi FE_{Sadness}$ was 1.8 when presented with ΦHF_{LO} and 3.71 when presented with ΦHF_{HI} (see Figure 7.b). The corresponding subjective value $\Psi FE_{Sadness}$ (i.e. Ψmin) was plotted according to 2.76. This value corresponded with the marginal means of 1.8 and 3.71. Consequently, functional measurement plots allow having direct access to the internal scale range associated with the effect size of the Facial and haptic information, FE and HF, on the Evaluation of emotional dimensions (i.e., the difference between Ψmin and Ψmax). Unlike classical graphs (Figure 6) that plot it as a function of the physical stimulus Φ continuum (Figure 7).

To access to the integration function, we need to collect experimental data on the participants' evaluation of the unimodal and bimodal cues and to perform functional measurements. Response patterns of the factorial plots must then be analyzed both visually and statistically to identify the algebraic rules [20]. For example, a parallelism pattern in the factorial plots supported by significant main effects on both factors and non-significant interaction between them is a signature of additive-type rule. A fan pattern in the factorial plots supported by a significant interaction between the both factors is an indicator of multiplying-type integration rule.

Factorial plots were examined for each measured emotional dimension:

Valence: Figure 7.a plots participants' Valence ratings as a function of their internal scale of FE (subjective values Ψ of FE). The plots show a parallel pattern between ΦHF_{LO} and ΦHF_{HI} conditions. We compare both internal scale ranges, of FE and HF, within the group of participants. We found a greater effect of FE (M=2.5, SD=0.76), compared to the effect of HF (M=0.38 SD=0.25), on perceived Valence [$t(20) = 10.79$, $p<0.0001$].

Arousal: Figure 7.b plots participants' Arousal ratings as a function of their internal scale of FE (subjective values Ψ of FE). The plots show a parallel pattern between ΦHF_{LO} and ΦHF_{HI} conditions. Data showed a similar effect of FE (M=0.54 SD=0.53), compared to the effect of HF (M=1.18, SD=0.73), on perceived Arousal [$t(20) = 2.75$, $p=0.012$].

Dominance: Figure 7.c illustrates participants' Dominance ratings as a function of their internal scale of FE (subjective values Ψ of FE). The plots a show parallel pattern between ΦHF_{LO} and ΦHF_{HI} conditions.

The comparison of FE and HF internal scales revealed a larger effect of HF (M=0.66 SD=0.74), compared to the effect of FE (M=1.76 SD=0.69), on perceived Dominance [$t(20) = 4.8$, $p<0.0001$].

The observed parallelism in the plots, supported by non-significant interaction terms, indicates an **adding-type integration rule** between FE and HF for the evaluation of each of the three emotional dimensions [20].

Relative Range Index (RRI) was computed to measure the

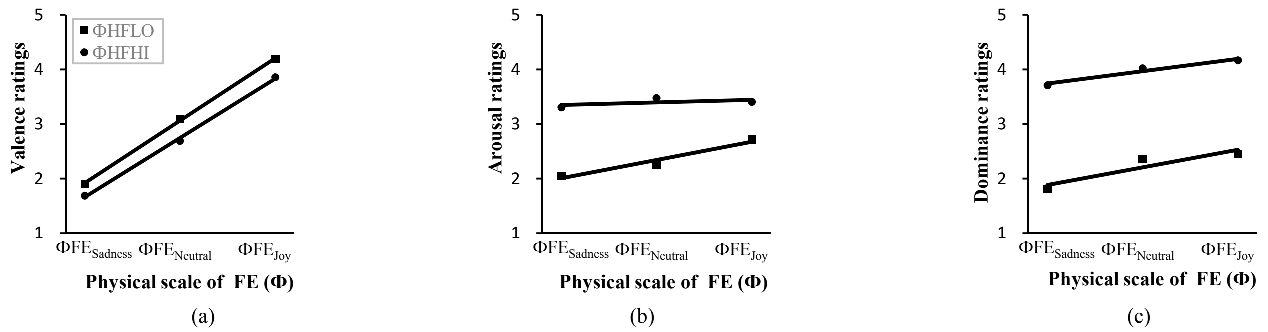


Fig. 6. Perceived emotional dimentions (a:Valence, b:Arousal, c: Dominace) as a function of the physical scale of Facial Expression (FE) and Haptic feedback Behaviour (HF).

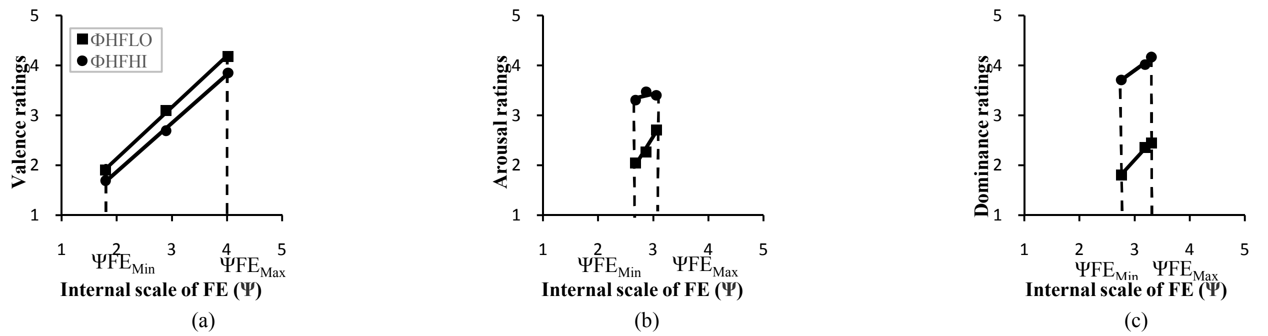


Fig. 7. Perceived emotional dimentions (a:Valence, b:Arousal, c: Dominace) as a function of the subjective scale of Facial Expression (FE) and Haptic feedback Behaviour (HF)

relative importance of each variable in magnitude estimation of each emotional dimension [34]. In this study, RRI was calculated for each participant as the ratio of the internal scale range of FEI ($\Psi FE_{max}-\Psi FE_{min}$) to the sum of two internal scale ranges of FEI and MS (ΨFEmax–ΨFEmin + $\Psi HF_{max}-\Psi HF_{min}$). The RRI of FEI relative to HF is 0.84 for Valence, 0.34 for Arousal and 0.23 for Dominance. The ANOVA showed that RRI differed significantly across groups [$F(2, 40) = 59.12$, $p<0.0001$], and post hoc tests (LSD test with a significance threshold set to $p < 0.05$) revealed a significant difference between Valence' RRI and Arousal' RRI. Significant difference between Valence' RRI and Dominance' RRI was also found. The difference of Arousal and Dominance RRI was not statistically significant. This index indicates that FE is over weighted compared to HF to evaluate Valence. Whereas the opposite was found for Arousal and Dominance (overweighting of HF).

In summary, results showed that the psychological scale was different across the three emotional dimensions. It reflects that the valuation process depended of the evaluated dimension for the studied emotions. The facial expression scale was larger for the Valence dimension. The haptic feedback scale was large for the Dominance dimension. The two scales were similar for the Arousal dimension. Functional measurements revealed that participants based their judgment on the haptic feedback (i.e. handshakes) and facial expression to evaluate each of the three emotional dimensions. For the three emotional dimensions, participants integrated these two sources of information according to an adding-type rule. They integrated Arousal dimension according to an averaging-type integration rule RRI highlighted that the relative importance of each modality was different across the emotional dimensions. Subjects gave more importance to facial expression when evaluating Valence (**H2**). Moreover, they gave more importance to haptic feedback when evaluating Arousal, and Dominance (**H3**). Several studies investigated how people exploit the tactile and visual modalities to perceive and recognize emotions [35]. The general conclusion of these studies was that the face is more important than the other modalities for judging the Valence of prototyped emotions. However, due to direct physical contact, haptic feedback is more efficient to communicate Arousal and Dominance[36][37][23]. These results demonstrated that combing haptic feedback facial expressions enhance the quality of emotion communication toward a user. It also permits to display a larger panel of emotion dimension levels by combining the two modalities. Finally, we can conclude to convey the richness of this multimodality the design social robots must jointly exploit facial and haptic nonverbal cues.

V. Conclusion

Advances in robotics are making robots more and more presented in humans' lives. To enhance human-robot interactions, robots must be able to recognize and display affective cues. In fact, emotions play a major role in human's life. They influence the way we perceive the word and how we take decisions. Affective communications is largely nonverbal. Therefore, it is necessary to study how people perceive affect displayed by a robot trough different nonverbal channels.

In this study, we examined how a group of participants combined facial expressions and handshaking with a humanoid robot to evaluate emotional dimensions (i.e. PAD). To highlight on this combination process, we performed Functional Measurement analyses. This method gave access to the cognitive process the group of participants. Results revealed that for the studied facial expressions and haptic feedback, participants based their judgment on both modalities when evaluating the emotional dimensions. Moreover, participants gave more importance to facial expressions in Valence evaluation. They gave higher importance to haptic feedback when evaluating Dominance. The two sources of information were equally exploited during Arousal evaluation.

Beyond providing additional knowledge about the psychology of human touch communication, this study should contribute to design an effective human-robot emotional communication. The use of the two modalities will support the communication of the three affective dimensions according to the context of the interaction between the robot and the user. For example a handshake can be used to communicate different levels of Arousal when communicating positive emotion (i.e. joy) using facial expression.

Using touch, like handshakes, can communicate other social aspects than emotions. For instance, touch provides an effective means for influencing people's social behaviors affecting people's attitudes toward specific tasks, and creating bonds between people [38], [39], [15], [40]. Future works should focus on the study the effect of robot haptic feedback, on such social aspects displayed by the robot.

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