Assessing Postural Control for Affect Recognition Using Video and Force Plates

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***Abstract*—Postural control is a dynamical process that has been extensively studied in motor control research. Recent experimental work shows a direct impact of affects on human balance. However, few studies on the automatic recognition of affects in full body expressions consider balance variables such as center of gravity displacements. Force plates enable the capture of balance variables with high precision. Automatic video extraction of the center of gravity is a basic alternative, which can be easily accessible for a wide range of public applications. This paper presents a comparison of balance variables extracted from the force plate and video processing. These variables are used to capture the bodily expressions of participants in a public speaking task designed to elicit stress. Results show that the variability of the center of gravity displacements from the force plate and video are related to negative emotions and situation appraisals. The power spectrum density broadness of the center of pressure from the force plate is related to Difficulty Describing Feelings, an important factor from a dispositional trait of Alexithymia. Implications of the use of such methods are discussed.**

***Keywords*— bodily expression of emotion, force plate, video processing, center of gravity, center of pressure, balance**

I. Introduction

Affective Computing researchers are paying increasing attention to the whole body channel [1]. This increased interest has resulted from the description of new empirical results in psychology that show the relevance of considering the whole body in non-verbal affective expressions [2]. Another reason for this interest in bodily expressions of emotion is the availability of softwares for automatic bodily analysis with affordable technologies such as webcams, inertial measurement units (Wiimote) and depth cameras (Kinect) [3]. Those solutions enable the capture and analysis of body movements in ecological set-ups [4]. More accurate and expensive systems such as optical motion capture system (e.g., Vicon) are also becoming popular in laboratory settings. Underused in body affect studies, force plates are platforms for measuring ground reaction forces. Force plates exist with different levels of precision (from a publicly available Wii balance board to industrial AMTI force plates used for advanced laboratory studies of postural control).

As collected data accumulate, results and interpretations of affective bodily reactions in situations are still inconsistent [1]. The high number of degrees of freedom of the whole body makes it difficult to compare the observations from different studies. Static body configuration [4], movement types [5], [6] and movement qualities [5], [3] are all potentially relevant for studying how the body expresses emotions in different interactive contexts. A proposed approach to studying this topic consists of three main steps [7]: 1) the extraction of low-level elements (positions, accelerations, silhouette, etc.), 2) the computation of intermediate features (quantity of motion, motion smoothness, leaning, etc.), and 3) data reduction. Intermediate elements in this process have to be relevant and meaningful in enabling further interpretation. The determination of appropriate intermediate level variables is a key issue for whole body affects recognition.

This article proposes the consideration of postural control variables as intermediate level variables for the analyses of affect in whole body expressions. Unlike the traditional static view of posture, postural control is dynamical. Even when apparently immobile, our body subtly oscillates. This sway can be impacted by different variables such as aging and attention [8]. A growing body of works shows the direct impact of affect on postural control [9]. Behaviors such as "freezing" when facing a threat can be detected using postural control analysis [10]. Human balance is assessed by analyzing Center Of Gravity (hereafter called "COG") or Center Of Pressure (hereafter called "COP") displacements [8]. Today, body movement features are increasingly and successfully taken into account in emotional expressions recognition [11], [12]. However, postural control is a specific process that should be distinguished from the broad category of body movements. Only a few works in affective computing use these specific variables [1], [13].

Laboratory recordings of motion capture data can be used for extracting the COG but are not available to the general public. Sophisticated force plates are difficult to setup outside laboratories. In this paper, we also consider video as it is simple to set up and is widely available.

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The purpose of this article is threefold: 1) Introduce COG and COP as relevant variables for the recognition of affect in standing situations, 2) Propose and evaluate a simple video extraction technique of the COG compared with precise force plate data, 3) Illustrate with data collected in a stressful experimental setup how the COG provides relevant information for processing spontaneous expressions of emotions, which might feature subtle movements and signals.

II. Background

A. Postural control studies and affect

Posture in conversational research is traditionally considered as a static body configuration. In his Posture Scoring System, Bull defines a posture as "any movement which is taken up and maintained for at least one second" [14]. In the Body Action and Posture Coding System (BAP), "A posture unit represents the general alignment of one or a set of articulators (head, trunk, arms) to a particular resting configuration" [6]. In both of these coding schemes, gestures are defined as movements occurring on top of static body configurations. These body configurations can convey specific emotions [15], action tendencies [16] or the intensities of certain emotions [4].

In motor control studies, posture is defined as, "the body automatic stabilization in the gravity force field in a standard position specific to the species" [17]. Postural control is therefore the dynamical process by which equilibrium is maintained. This process is assessed by analyzing COG or COP displacement in the horizontal plane [8]. It is important to note that horizontal and vertical forces are not relevant variables for the study of postural control in quiet stance situations contrary to gait analysis. Several theories exist to explain this sway: sway might be a consequence of noisy processes within the human neuromotor system, a reflection of an active search process or an output of a control process of stabilization of the whole body as an unstable structure [18].

Affects' impact on postural control is a relatively new field of research in the motor control domain [9]. Participants are usually standing on a force plate while pictures designed to elicit emotions are displayed in front of them. Databases of emotional pictures such as IAPS are commonly used [19]. Hypotheses about the impact of emotions on body signals are often driven by motivational theories [20] or the action tendency component of emotions [21]. Negative stimuli can trigger flee behaviors or freezing behaviors. Positive stimuli might attract participants or induce a ''do anything'' motor program [22].

Postural freezing behaviors are usually detected in the center of the pressure signal, which shows a decrease in amplitude and an increase in frequency when such behaviors occur [23], [10]. Results from [9] suggest that this increase in frequency is modulated by arousal. No consistent results are available about the type of COP displacement (approach or avoidance) or the direction of this displacement (Anterior-Posterior AP or Medial-Lateral ML). An alternative to COG or COP displacement analysis is the use of electromyography (EMG) data to measure muscle contractions [24]. Horslen and Carpenter argue that methodological issues are responsible for these inconsistent results such as sampling duration. Another limitation of such studies is that they do not consider ecological situations. In affect recognition, only few studies include postural control variables as descriptors [13].

The above-mentioned literature from motor control studies suggests a dynamical subtle impact of emotion on balance. This new way of apprehending posture is of particular interest when detecting users' emotions in an upright stance.

B. Automatic extraction techniques in video

Automatic video analysis techniques are used to infer the emotional behaviors of humans from video sequences. Several cues can be extracted from images in order to extract physical characteristic related to emotional expressions. In order to extract these cues, a video processing platform (e.g., EyesWeb [3]) can be used. For example, Castellano, Villalba and Camurri [25] extracted from participants five different expressive motion cues: quantity of motion, contraction index of the body, velocity, acceleration and fluidity of hands. Quantity of motion and contraction index were the most significant cues in differentiating between the selected acted emotions. Cues such as position, size, angles and movement between frames from specific body regions (head and hands) have also been proposed [26].

Sanghvi et al. [27] analyzed the patterns of postural behavior of children interacting with a robot by measuring the orientation of the silhouette of their upper body and the curvature of the contours of their back. The authors found that patterns of postural behavior could be used to accurately predict the engagement of the children. Bonardi, Truck and Akdag [13] proposed an emotion detector of an actor's performance. Its stability, the COG, the contraction surface and the movement duration were computed from the silhouette. The stability and the COG provided reliable insights on whether the performer did put himself at risk.

Real-time video cues processing is also very important for improving the interaction between users and machines. Friber [28] proposed a real-time algorithm to analyze emotional expression in musical performance and body movements. A fuzzy analyzer was implemented to consider the quantity of motion.

Recently, some authors investigated the use of motion capture data in order to estimate emotional behaviors [29]. Mental states and emotions were estimated from video-based 3D articulated pose estimates. Tan, Schöning, Barnes, Luyten and Coninx [30] proposed a system that used motion-captured data collected with a Kinect in order to analyze user's postures during a game.

III. Estimation of Postural Control Variables

The studies cited in the previous section suggest that computing postural control variables is relevant for affect recognition. Force plates are optimal devices for studying balance with high precision, but they are difficult to setup outside of laboratory settings. Video is a good alternative when the ecology of the interactive situation is essential. No study compares these two means of estimating COG. In this section, we describe methods to estimate the COG with these two complementary devices.

A. Force plates

The COG is the point of the resultant of gravity forces. The COG is independent of velocity and its vertical projection in the horizontal plane is called the Gravity Line (Hereafter called "GL") (Fig. 1). Equilibrium is obtained by maintaining this GL within the base of support. The COG can be extracted via kinematic methods by combining segment positions and inertial parameters [8]. Stabilographic methods enable the determination of the GL from force plate data (the COP). The simplest method is equivalent to a low pass filter with the cut-off frequency determined by anthropometric data [31].

The COP is "the position of the resultant vertical component of the ground reaction force applied to the body at the ground surface" [32]. The COP is related to the GL and depends on the acceleration of the body. COP is mostly used in motor control studies because it is directly measured by the force plate and it includes more information than the COG. The COP is computed from the moments in the horizontal plane caused by the ground reaction force on the force plate. The COP can be decomposed into two components: *rambling,* which is the reference point migration, and *trembling,* which is the COP migration around the reference point [32]. Rambling is similar to the GL and has lower frequencies and larger amplitudes than trembling. Trembling is due to "apparent intrinsic stiffness" when excursions are not too large.

In this study, we calculated the COG signal from the COP signal with the method used in [31], which requires knowledge of only three anthropometric values: height, weight and the gravity center height of participants. Height and weight have to be measured and gravity center height can be estimated for males (57% of the height) and females (55% of the height) [17] .

B. Video

For each video sequence, we compute the COG in the media-lateral plane directly from the human silhouette. In order to segment the human silhouette, a background subtraction algorithm is used. Since our background is static, we use a simple background subtraction algorithm that calculates the absolute frame difference between a reference empty scene and the current image.

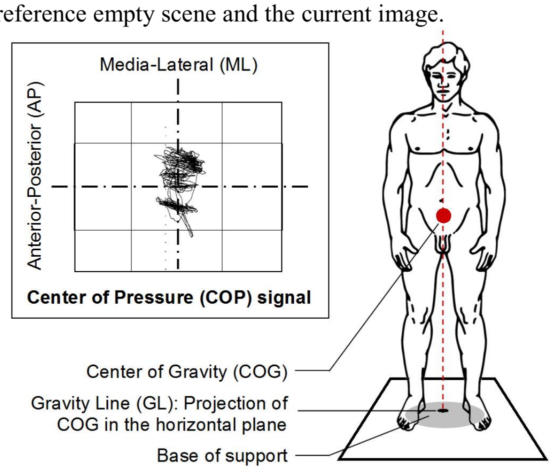

Fig. 1. Representations of the COG, the GL, the base of support and displacements of the COP

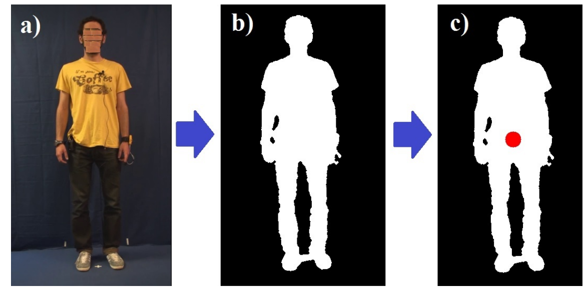

Fig. 2. The COG extracted from the human silhouette. The images are, respectively: (a) the captured image, (b) the extracted silhouette and (c) the COG represented by a red circle.

In order to provide more robustness to changes in lighting conditions and shadows, the background subtraction algorithm is computed using the HLS space, similar to the method proposed in [33].

After the foreground silhouette is obtained, the COG point $C_g = (x_g, y_g)$ is obtained by computing the following equations [34]:

$$x_g = \frac{\sum_i^N x_i}{N}, \qquad y_g = \frac{\sum_i^N y_i}{N}$$

where N is the number of pixels in the human foreground silhouette. Fig. 2 shows an example of an extracted human silhouette and the estimation of its COG.

IV. Method

This section presents a protocol designed to elicit stress in participants who are standing while presenting themselves. The first aim of this study is to compare signals (the COG from the force plate and video and the COP from the force plate). We expect that video estimation of COG accounts for large displacements of COG displacements in the media-lateral plane but not for subtle displacements unlike force plate estimation. The second aim is to study postural control's links to emotional states and traits. COG and COP signals are analyzed in the media-lateral plane.

Data were collected from 7 healthy male and 12 female university students. For males, the mean age was 26.4 years ± 7.1 (mean ± SD). For females, the mean age was 27.1 years ± 4.8 (mean ± SD). Each participant filled out a consent form. In the following, we only summarize the method that is described in detail elsewhere [35].

Participants were subjected to a public speaking task adapted from the Trier Social Stress Test [36]. This procedure is used to induce stress. Participants were told that they had to present themselves in front of two assessors. The task included a two-minute reading, a one-minute instructions reminder, a five-minute self-introduction speech and two feedback sessions from the two assessors. The assessors' feedback and questions were about the participant's performance. The two assessors showed either a positive or a negative attitude to the participants. Each participant received the negative feedback first and the positive feedback second. The whole task lasted 20 min on average, for a total duration of 380 min for the corpus.

In order to assess emotional states and traits, participants filled out different validated questionnaires. For this study, we focus on four questionnaires that assess states. Ten minutes before the task, threat and challenge appraisals (Appra) were measured by four questions on a seven-point Likert scale [37]. Just after the task, each participant's anxiety state (STAI-S) was measured by the STAI [38]. Positive (PA) and negative (NA) emotional states were measured by the PANAS [39]. Two personality traits are also considered in this study. Alexithymia was assessed with the TAS-20 [40]. This trait is composed of three subscales: Difficulty Identifying Feelings (DIF), Difficulty Describing Feelings (DDF), and Externally Oriented Thinking (EOT). Anxiety as a disposition (STAI-T) was measured by the STAI [38]. Not studied yet, traits associated with emotion regulation can be correlated with balance variables in arousing situations.

Video data was recorded using a Sony HDR-CX550 camera at 25 fps in full HD. COP data was recorded with an AMTI AccuGait force plate at 50 Hz. The force plate was hidden within a stage covered by a blue sheet. Another blue sheet was placed on the wall behind the stage to provide a uniform background. Participants were asked to stand close to a white cross in the middle of the force plate. Video and force plate data were synchronized manually according to a time marker (a kick on the ground).

A video or force plate sequence represents data for a participant in one of the experimental phases (reading, listening, presenting, negative feedback or positive feedback). Two participants' data were lost due to force plate malfunction. Seven sequences were lost due to subject foot misplacement (outside of the force plate). The resulting corpus is composed of 78 sequences in total.

V. Results

A. Force plate and video signals comparison

1) Correlations in the time domain

Table I shows averaged correlations between the COG time series from the force plate and video for each task phase. For all phases, correlations were very strong and significant ($r > 0.85$, $p<0.001$). A Kruskal-Wallis test (data are not normally distributed) revealed no statistically significant difference between the experimental phases ($X^2(4) = 2.343$, $p = 0.673$).

The majority of the COG signal from the force plate is present in the COG video signal (total $r^2 = 80\%$). The lost variance might be due to noise in the video extraction process. Sources of noise for video processing include loose clothes, silhouette artifacts due to shadows and asymmetric occlusions. Another potential source of lost variance is the resolution of the video recordings. As the camera is placed three meters from the participant, one pixel of the silhouette represents approximately two millimeters of the silhouette.

TABLE I. PEARSON CORRELATIONS BETWEEN COG TIME SERIES FROM VIDEO AND FORCE PLATE (N = NUMBER OF SEQUENCES)

	Phases of the public speaking task					
	Read	*Listen*	*Instructions*	*Negative Feedback*	*Positive Feedback*	*Total*
N	*15*	*14*	*17*	*17*	*15*	*78*
r	.889	.937	.879	.911	.856	.894
sd	.083	.046	.125	.090	.156	.100

For COP and COG displacements, there is a relation between displacement amplitude and frequency range [32]. Relatively high frequencies represent small amplitudes and vice versa. It is very important to know if COG signals extracted from videos are sensitive to only low frequencies due to low resolution as most balance studies use frequency variables.

2) Frequency analysis

Reading phases are not included as participants hold a book in their hands. A COP signal is composed of very low frequencies (under 0.05 Hz), which are sensitive to signal length [41]. In fact, 1/T (T being the sequence length) determines the lowest frequency represented by a Fourier transform (FFT). For this analysis, frequency spectrums are presented only for a fixed window [1/Tmin, 1] Hz, where Tmin is the smallest length of our sequences (Tmin = 37 s, lowest frequency represented = 0.027 Hz).

Postural control is affected by anthropometric characteristics and foot placement [8]. For standardizing data between subjects we divided the signals by subject height. For each sequence, power spectral density (PSD) of COG from video (COG video), COG from force plate (COG FP) and COP from force plate (COP FP) were computed with a fast Fourier transform. The PSD were normalized with respect to the individual peak values of the PSD. These normalized data were then averaged for the group [32].

Figure 3 suggests that the COG extracted from the video did not contain frequencies above to 0.2 Hz. As explained previously, this is probably due to the low resolution of the video recordings. To confirm this, Table II shows average frequency bands that contain 80% of the spectral power (hereafter called "F80"). This measure is considered as the best measure to characterize spectrum broadness [18].

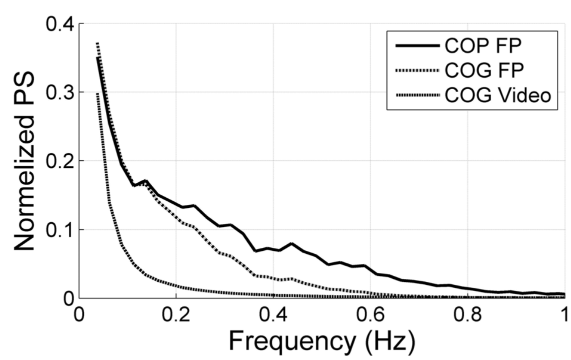

Fig. 3. Normalized power spectrums of the COG from the video and the force plate and the COP from the force plate.

TABLE II. F80 FOR COG FROM THE VIDEO AND THE FORCE PLATE AND COP FROM THE FORCE PLATE AND THEIR PEARSON CORRELATIONS

		F80 (n=63)		
		COG Video	*COG FP*	*COP FP*
	mean	.146	.224	.437
	sd	.066	.088	.338
COG Video	r		.264	.058
	p		.307	.826
COG FP	r			**.595** [a]
	p			**.012**

a. Correlation is significant at the 0,05 level

Wilcoxon signed-ranked tests were used to compare F80 two-by-two (non-normality and dependent samples). All means were significantly different ($Z = -5.765$, $p < 0.001$ between F80 CG Video and F80 CG FP, $Z = -6.805$, $p < 0.001$ between F80 CG Video and F80 COP FP and $Z = -6.846$, $p < 0.001$ between F80 CG FP and F80 COP FP). This confirms that the COG extracted from video contains significantly less high frequencies than data from the force plate. Also, only F80 COG FP and F80 COP FP are correlated significantly. Taken together, these results meet our expectations. Most of the COG signal from the video shared with the force plate signal (80%) is located at frequencies under 0.1 Hz. This part of the signal represents large COG displacements. Subtle displacements at higher frequencies are not present in the video probably due to low resolution.

3) Comparison with the Quantity of Motion (QoM)

We included in our analysis a comparison between the variability (standard deviation) of our three measures with a classical measure of overall movement activity [25].

Table III shows a high coherence between COG from the video and the force plate and COP from the force plate (more than 90%). It also shows a moderate correlation between QoM and the three other variables (30% of shared variance).

B. Emotional states and traits

Table IV presents correlations between the standard deviation (std) and F80 of our three signals and emotion states and traits variables. The standard deviations from our three signals are correlated significantly for appraisal and negative emotions. Participants who appraised the situation as a threat rather than a challenge, or experienced the situation with more negative emotions had higher COP and COG displacements than the other participants. F80 of the COP from the force plate only correlates to the Difficulty of Describing Feelings. Participants who have difficulties putting words on their emotions (which is associated with poor emotional experiences) had larger spectrums. The absence of correlations between F80 of the two COG with Difficulty Describing Feelings shows the importance of the trembling component present only in the COP.

These results confirm in part our expectations. Human balance variability seems affected more specifically by negative experiences and perceived social threats. Only one subscale of assessed dispositional traits is associated with sway spectrum characteristics.

TABLE III. STD FOR COG FROM THE VIDEO AND THE FORCE PLATE AND COP FROM THE FORCE PLATE CORRELATED WITH QOM

		Standard Deviation (std) (n=63)		
		COG Video	*COG FP*	*COP FP*
std COG Video	r		**.996** [a]	**.971** [a]
	p		**.000**	**.000**
std COG FP	r			**.962** [a]
	p			**.000**
QoM	r	**.582** [a]	**.544** [a]	**.610** [a]
	p	**.023**	**.036**	**.016**

a. Correlation is significant at the 0,05 level

TABLE IV. PEARSON CORRELATIONS BETWEEN BALANCE VARIABLES AND EMOTIONAL STATES AND TRAITS

		COG Video		COG FP		COP FP	
		std	*F80*	*std*	*F80*	*std*	*F80*
Appra	**r**	**.754** [a]	-.081	**.720** [a]	-.204	**.755** [a]	-.078
	p	**.000**	.757	**.001**	.433	**.000**	.767
STAI-S	**r**	.457	.015	.405	-.257	.429	.144
	p	.065	.956	.106	.319	.086	.580
PA	**r**	-.409	.061	-.381	.414	-.325	-.095
	p	.103	.816	.131	.099	.203	.717
NA	**r**	**.552** [a]	.052	**.504** [a]	-.076	**.515** [a]	.175
	p	**.022**	.842	**.039**	.772	**.034**	.501
STAI-T	**r**	.285	.093	.243	-.086	.252	.452
	p	.267	.723	.348	.744	.329	.069
DIF	**r**	.102	.048	.076	-.330	.067	.233
	p	.696	.856	.771	.195	.800	.367
DDF	**r**	-.139	-.219	-.151	.006	-.197	**.641** [a]
	p	.594	.399	.563	.980	.448	**.006**
EOT	**r**	.232	.301	.258	-.091	.190	-.074
	p	.371	.240	.318	.728	.466	.778

a. Correlation is significant at the 0,05 level

VI. DISCUSSION

Our results show the relevance of COG analysis for affect recognition. Caution should be taken when estimation methods and devices are chosen. To study variability and large displacements, video is a relevant option, which is of particular interest when studying negative emotions and stressful situation appraisals. However, when subtle variations are important, video seems to be not precise enough, which is the case when freezing behaviors are of interest.

Freezing behaviors induces immobility (reduced standard deviation) and rigidity (increased mean power frequency) [10]. A COG video estimation method may not be able to differentiate between quiet standing and freezing standing in front of a threat as frequencies above 0.2 Hz are essential.

The moderate correlation between COG and the quantity of motion variable suggests how these two measures are complementary. Symmetric and vertical movements are not represented in the GOG, which makes it less sensitive to hand movements. Theoretical reasons also differentiate COG and quantity of motion as body sway activity cannot be considered as a measure of energy.

We attend to continue this work in several directions. This analysis has been done only for the medial-lateral axis; a study of the anterior-posterior axis is required to be able to generalize the analysis and underline complementarities. The insensitivity of video to small variations in this study is probably due to low resolution. How placing the camera in a vertical configuration or using a 4K camera (3840 pixels × 2160 pixels) could increase this sensitivity is another question. Another direction for future works is to investigate in more details the sway characteristics (e.g. structural properties [42]) as well as considering small windows of emotional expressions [12]. How discriminative are these variables for the perception of emotion is another interesting question which could be tackled by conducting a perceptive study [43]. Finally, another future direction is the study of balance in scenario eliciting positive emotions.

VII. Conclusion

The dynamical process of postural control is impacted by affect. A growing body of motor control studies encourages the consideration of COG variables when studying affect recognition. As Affective Computing often relies on ecological situations and end user applications, it is important to be able to compute such variables with affordable and widely used devices and methods. We compared two methods for COG estimation. The first method is based on force plates, which provide precise data but are hardly used in an ecological setup. The second method is based on video analysis, which is less precise but widely usable. To further show how relevant balance variables are for affect recognition, data were collected during a public speaking task, which induced stress. Results show that balance variables such as COG displacement variability are correlated to negative emotions and situation appraisals. The results also indicate differences between estimations methods. COG video estimation is relevant when studying relatively large variations. For more subtle variations, such as the detection of freezing behavior, researchers should consider using force plates.

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