Neurocoaching: exploring the relationship between coach and coachee by means of bioelectrical signal similarities

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***Abstract*— Coaching aims to unlock the human's potential, self-awareness and responsibility, improving the professional performances and the personal satisfaction. Its effectiveness is known to depend on the degree of bonding and mutual engagement of the coaching relationship. In this exploratory study we recorded synchronised EEG and SC data from both coach and coachee during 36 individual sessions, performed following 2 different coaching methods. Our principal aim was to investigate the temporal evolution of the bonding and the mutual engagement along the different steps of a session, by means of a "similarity" metric based on the DTW distance between signals (namely, S-TVM). We found significant differences between session phases for the EEG-related S-TVMs (BAR, BATR and AWI), with maximum values (defined as "tuning") all in the same phase, but differentiated between the two experiments. The results suggest a temporal concurrency of the engagement and emotional tunings, whose specific location seems to be a function of the coaching approach.**

I. Introduction

Nowadays, coaching is a widespread technique with about 47,500 professional coaches worldwide [1] operating in several different contexts, such as healthcare, sports, education and corporate groups [2]. Coaching can be defined as an helping relationship between a facilitator (coach) and a participant (coachee). Using a Socratic-type method (i.e. a cooperative dialogue, based on open questions), the coach aims to unlock the coachee's potential, self-awareness and personal responsibility, improving, consequently, his/her professional performances and personal satisfaction [3].

Professional coaches can follow either a well-defined theoretical model (e.g. the positive psychology- and the systemic-based coaching) or mix different models (the so-called eclectic coaching) [4]. An example of eclectic coaching is the *core coaching*. It consist on a face-to-face dialogue were coach and coachee are positioned on a conformable armchair. During the session the coach puts some questions to the coachee about his/her problematic events. The related answers are investigated by the coach using kynesiologic tests [5], in order to assess their (underlined) emotional content.

An example of systemic-based coaching is the *systemic costellation*. It consists on a scenic representation of problematic events, localised in both the space and the time. Basically, the coachee identifies a specific objective and 5 different ways to reach it. These steps are first represented on 5 papers and then physically positioned on the floor to form a so-called *costellation*. Finally, the coachee put himself/herself on each paper and start describing what he/she is feeling [6].

Besides the different available approaches, some authors reported that the effectiveness of the whole coaching process strongly depends on the overall coach-coachee relationship, in terms of bonding and mutual engagement [7]. These features have been mainly detected using indirect measures (self reports and psychometric assessments) at the end of the sessions, but there are also few examples of direct measurements. In [8], they used the functional Magenetic Resonance Imaging (fMRI) to test the effects of 2 different coaching styles on Blood Oxygen Level Dependent signal, while in [9] they collected in a pre-post experimental design several Electroencephalographic (EEG) metrics to assess the effectiveness of a coaching journey.

By the best of our knowledge, no studies have explored so far the evolution of a coaching session using bioelectric measures, in terms of continuously measuring the above mentioned bonding and mutual engagement during the time.

In this exploratory study, we recorded synchronized EEG and Skin-Conductance (SC) data of both coach and coachee during several coaching sessions, performed following two different approaches: the systemic costellations and the core coaching. Our principal aim was to investigate the temporal evolution of a "similarity" measure between coach's and coachee's bioelectric signals, as a possible indicator of a mutual engagement and bonding. In fact, resonance mechanisms and synchronized bioelectrical patterns have been previously observed during social interactions - expecially those that produce a sort of "bonding" between the subjects [10].

II. Methods

A. Study population and experimental design

The study comprised of two different experiment: the first focused on the core coaching, while the second on the systemic constellations. All the coachees were students just exiting the university and approaching the labour market. Two professional coaches (A. G. and G. S., for, respectively, the first and the second experiment) led them during an exploration of their future objectives, their ambitions, their

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plans to reach them and the ways to overcome the possible obstacles.

The study protocol was approved by the ethical committee of Università IULM and informed written consent was obtained from each participant before starting the experiment.

1) Experiment 1: Sixteen students, (8 Males, mean age 24 ± 0.96 years, range $23-26$) were enrolled. A professional coach (A. G.) led the experiment following the core coaching approach. The sessions were approximately 90 minutes long and consisted of 3 main phases. In phase 1 the relationship between coach and coachee is created. In phase 2 the coach assesses the road to reach the objectives using kynesiologic tests. In phase 3 the coachee discusses his/her feelings after the session.

2) Experiment 2: Sixteen students (8 Males, mean age 23.25 ± 1.48 years, range $20-26$) were enrolled. A professional coach (G. S.) led the experiment following the systemic constellations approach. The sessions, approximately 45 minutes long, consisted of 4 phases. In phase 1 the relationship between coach and coachee is created and the choices to be assessed are listed and represented on paper. In phase 2 the papers are placed to form the constellation. In phase 3 the coachee moves inside the constellation to reach the goal in the preferred way. In phase 4 the coaching session is evaluated and the action to reach the coachee's goal discussed.

B. Instrumentation

Each coaching session was video-taped using two webcams (LifeCam Studio by Microsoft, Inc.).

The EEG was recorded using a 14 channels Epoc (Emotiv Inc.) device, with a sample frequency of 128 Hz and a resolution of 14 bits. The device was in-house modified in order to improve its signal quality and mechanical stability, according to [11]. The original water-based electrodes were replaced with gel-based Sn electrodes, embedded in a medical grade EEG cap (Taomed, s.r.l.). Reference and ground electrodes were replaced with two earclips at the left and right earlobes.

SC signal was recorded using a Shimmer GSR+ (Shimmer Sensing, Ltd.) with a sample frequency of 128 Hz and a resolution of 12 bits. According to the literature [12], SC was measured using the constant-voltage mode (0.5 V) from 2 Ag/AgCl electrodes placed on the index and ring finger of the non-dominant hand.

Coach and coachee recordings were temporal aligned using their UTC timestamps and the events corresponding to the session phases were manually placed looking at the video recordings. The duration of each event was set to 120 s.

C. EEG processing

EEG signals were processed using Matlab (The Mathowrks, Inc.) and the EEGLab toolbox [13], according to the following pipeline:

- Band-pass filtering between 2 and 48 Hz (-6 dB cut-off at 1 and 49 Hz);
- Notch filtering at both 50 and 100 Hz, in order to reduce the powerline noise;
- Rejection of extreme sample points using an amplitude threshold ($\pm 100\ \mu V$) and a gradient threshold ($\pm 10\ \mu V/s$);
- Independent Component Analysis (ICA) decomposition using SOBI algorithm that exhibits the best performance with respect to the majority of artefact types [14];
- Classification of Independent Components (ICs) using the 7-classes neural-network classifier ICLabel [15] that gives for each IC the probability (`Pr`) to be expression of `brain`, `muscle`, `eye`, `hearth`, `line noise`, `channel noise` or `other` electrical activities.
- Identification of not-artifactual ICs using the decision rule: `Pr(brain)>0.70 OR (Pr(brain)>=0.50 AND Pr(brain)+Pr(other)>=0.70`.
- Rejection of artifactual ICs and back-projection to the original sensor space to obtain a filtered EEG signal;
- Epoching according to the session phases.

Due to the rejection of extreme points, homologous epochs related to each pair of coach and coachee could have different lengths. From each epoch, the Beta over Alpha Ratio (BAR), Beta over Alpha plus Theta Ratio (BATR) and Approach-Withdrawal Index (AWI) were computed.

In order to compute the metrics, various EEG channels were filtered in different bands and their instant power was computed. Given an individual alpha frequency (IAF) conventionally set at 10 Hz, Theta (θ), Alpha (α) and Beta (β) bands are defined as: $\theta = [IAF-6; IAF-2]$, $\alpha = [IAF-2; IAF+2]$ and $\beta = [IAF+2; IAF+16]$ [16]. Then, we applied a time-frequency approach: from each channel we estimated the spectrogram using a Short-time Fourier transform (STFT) with a 1 s long hamming window and 50% overlapping. Spectral bins corresponding to the selected band (either θ, α or β) were summed (obtaining the channel instant power) and selected channels were averaged together (obtaining the group instant power). Finally, a logarithm transformation was applied in order to mitigate the skewness of the power values [17].

BAR is obtained as the ratio between the α and β group powers, considering as a group all the channels. Likewise, BATR is the ratio between β group power and the sum of α and θ group powers. BAR has been previously associated to emotional arousal [18], while BATR has been previously adopted as Engagement Index [19]. AWI is obtained as the difference between α-right and α-left group powers, considering as left group the left frontal electrodes (Fp1, F7, F3) and right group the right frontal electrodes (Fp2, F8, F4). It has been previously associated with the approach-withdrawal behaviour that mostly correlates with the emotional valence [20].

All metrics were z-score transformed according to the mean value and the standard deviation of the entire signal, as in [21].

Resonance mechanisms and synchronized bioelectrical patterns have been previously observed during during social interactions - expecially those that produce a sort of "bonding" between the subjects [10]. Since coach and coachee's recordings were temporal aligned in the pre-processing steps, as a syncronization measure we proposed a "similarity" measure between the corresponding aligned biosignals.

For each phase and each couple, we computed the "similarities" between coach and coachee TVMs using the Dynamic Time Warping (DTW) technique. DTW is a shape-based distance measure that finds the best similarity of two signals applying a temporal warping (i.e. contraction or dilatation). The temporal stretching allows to find an optimal path (the non-linear mapping of the most common local features) minimizing a proper distance metric between the wrapped signals [22].

DWT distance is formally computed as follows [26]. Let's define the distance matrix $\mathbf{D}$ coresponding to the signals $X = \{x_i\}_{i=1}^{m}$ and $Y = \{y_i\}_{i=1}^{n}$ as:

$$\mathbf{D} = \{d_{ij}\}_{i=1,j=1}^{i=m,j=n} \tag{1}$$

where the element $d_{ij} = dist(x_i, y_j)$ is the proper distance (e.g. Euclidean, Manhattan) between the points x_i and y_j. Let's define the warping path $W = \{w_i\}_{i=1}^{K}$ as a set of elements $w_i \in \mathbf{D}$, such as $K \in [\max\{m,n\},\ m+n-1]$, $w_1 = d_{11}$ and $w_K = d_{mn}$ [22]. Additionally, let's the w_k be adjacent in $\mathbf{D}$, namely, the position of the elements in $\mathbf{D}$ corresponding to each couple (w_i, w_{i+1}) have a unitary Manhattan distance. The DTW distance is finally computed as:

$$DWT = \min\left\{\sqrt{\sum_{i=1}^{K} w_i}\right\} \tag{2}$$

In the present work, the chosen distance metric was the Euclidean's one. The application of DWT in EEG signal processing is quite usual and its feasibility to identify EEG waveform has been previously demonstrated [23]. As "similarity" measure (S-TVM) we chose the inverse of the DTW distance.

D. SC processing

SC signal was processed using Matlab. Since its maximum bandwidth is around 0.37 Hz [24], it was first downsampled to 1 Hz. Then, the artefacts correction and the Skin-Conductance Level (SCL) decomposition were applied, as previously described in [21]. We selected SCL because is considered a robust estimation of the emotional arousal [25].

Similarly to EEG, S-TVM was computed for the SCL, epoched and z-score transformed according to the entire duration of the recording.

E. Statistical Analysis

The statistical analyses were performed in Matlab. Since the assumptions of normality and homoschedasticity were not met (as confirmed by the Kolmogorov-Smirnov and Bartlett tests), for each S-TVMs, we computed a Kruskal-Wallis test using the phase as factor to evaluate how the "similarity" between coach and coachee changed along the session. As post-hoc analsyis, we applied the Wilcoxon sign-rank tests, Bonferroni-corrected for multiple comparisons.

III. Results

After the processing steps, some subject were rejected due to the excessive noise or for missing either the EEG or the SC recordings.

The final population of experiment 1 comprised of 14 subjects with EEG data (7 males, mean age 23.43 ± 1.50, range $20-26$ years) and 7 with SC recordings (3 males, mean age 22.57 ± 1.51, range $20-25$ years). Significant differences $(p < 0.05)$ were found for all EEG-related S-TVMs. Post hoc analysis confirmed significant $(p < 0.05)$ differences between all the phases for AWI, BAR and BATR S-TVMs. No differences were found for the S-TVM of the SCL.

The following Table I reports the descriptive statistics (mean $\pm$ standard deviation) for the EEG-related S-TVMs.

TABLE I
MEAN AND STANDARD DEVIATION OF THE EEG-RELATED S-TVMS

	Phase1	**Phase2**	**Phase3**
AWI	0.003±0.003	0.001±0.000	0.008±0.013
BAR	1.156±1.685	0.086±0.036	10.260±22.222
BATR	0.832±0.933	0.096±0.042	3.853±5.439

The final population of experiment 2 comprised of 8 subjects with EEG data (5 males, mean age 23.43 ± 1.50, range $23-25$ years) and 11 subjects with SC data (3 males, mean age 23.91 ± 0.83, range $23-25$ years). Significant differences were found for all S-TVMs $(p < 0.05)$. Post hoc analysis confirmed a significant difference $(p < 0.05)$ between phases: 1 VS 2, 1 VS 3 and 1 VS 4 for AWI; 1 VS 2, 1 VS 3 and 1 VS 4 for BAR; 1 VS 2, 1 VS 3 and 1 VS 4 for BATR. No differences were found for the S-TVM of the SCL.

The following Table II reports the descriptive statistics (mean $\pm$ standard deviation) for the EEG-related S-TVMs.

TABLE II
MEAN AND STANDARD DEVIATION OF THE EEG-RELATED S-TVMS

	Phase1	**Phase2**	**Phase3**	**Phase4**
AWI	0.011±0.006	0.001±0.002	0.001±0.003	0.002±0.003
BAR	2.287±2.010	0.123±0.349	0.278±0.787	0.240±0.444
BATR	2.017±1.917	0.129±0.365	0.131±0.371	0.209±0.390

IV. Discussion

In this exploratory study, we investigated the strenght of bonding and mutual engagement between coach-coachee during a coaching session. We evaluated two different coaching methods in two different experiments: the core coaching method (experiment 1) and the systemic constallations (experiment 2). As a measure of the strength of the coaching relationship, we proposed the S-TVM, namely the inverse DTW distance between EEG- and SC-related TVMs. EEG and SC correlates to emotional valence, emotional arousal and engagement are summarised in Table III.

In both experiments, the BAR S-TVMs showed significant differences between phases, while the SCL S-TVMs did not. This result seems inconsistent, since both SCL and

TABLE III

EMOTIONAL AND ENGAGEMENT CORRELATES OF SC AND EEG VARIABLES

Variable	EEG/SC	Correlate
SCL	SC	Emotional Arousal
AWI	EEG	Emotional Valence
BAR	EEG	Emotional Arousal
BATR	EEG	Engagement

BAR estimate the emotional arousal. A possible explanation could be found in the different sensibility of CNS (Central Nervouse System) and ANS (Autonomous Nervouse System) to the arousal. In fact, as an EEG-related metric, BAR is related to the CNS, while SCL is related to the ANS.

In experiment 1, the emotional "tuning" (that we defined as the highest similarity) of both valence and arousal components was found in the last phase, while in the experiment 2 (systemic costellations) in the first phase.

The BATR S-TVMs showed, similarly, a coherent behaviour: in experiment 1 the tuning was found in the last phase, while in experiment 2 in the first phase.

Both experiments showed a temporal concurrency between the emotional and the engagement tuning, but their position within the phases was different. This suggest that in experiment 1 the coach needed more time (i.e. both the phase 1 and 2) to finally reach the tuning, differently from experiment 2 where it was reached at the beginning of the session (phase 1).

These results need to be further investigated by a future confirmatory study, using different coaches, following the same coaching approaches, in order to exclude the confounding variable of the coach as such. Additionally, hyperscanning techniques would allow a finer analysis (e.g. sample-by-sample) of the proposed S-TVMs, in order to find possible tunings within each session phase. Finally, the correspondence between the tunings and the real perceived emotional/engagement similarities should be investigated using psychometric techniques.

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