Follow the Flow: A Prospective on the On-Line Detection of Flow Mental State through Machine Learning

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Abstract

Flow is a precious mental status for achieving high sports performance. It is defined as an emotional state with high valence and high arousal levels. However, a viable detection system that could provide information about it in real-time is not yet recognized. The prospective work presented here aims to the creation of an online flow detection framework. A supervised machine learning model will be trained to predict valence and arousal levels, both on already existing databases and freshly collected physiological data. As final result, the definition of the minimally expensive (both in terms of sensors and time) amount of data needed to predict a flow status will enable the creation of a real-time detection interface of flow.

Keywords: Flow, Machine Learning, Emotion Detection, Realtime Detection, Biosensors, Affective Computing

1. Introduction

Flow, or the optimal experience [1], is a fundamental status for all the fields relying on performance. However, one of the main challenges is linked to its very definition: it is a deeply personal experience, it manifests itself in different ways for each person, and it is easily interrupted by external interference. Therefore its objective detection and recognition are fraught with complexities. In the classical questionnaire-based approach, tools like the Flow State Scale [2], are submitted typically after, or right before, a possible flow situation (e.g., a sports competition), and in studies linking physiological recordings and flow, data are analyzed post-hoc [3,4].

Flow is considered to be connected to peak performances because both present the experience of peak moments [5], which proved to be a condition of particular interest in sports practice. The capability of recording flow in real-time with a more precise timeline would, as a result, increase athletes' self-awareness and help coaches and mental trainers.

This article proposes the construction of a Machine Learning (ML) model, allowing real-time analysis of the subject's physiological data, and providing a live indication of the flow status. This would allow the development of an application, with the potential of becoming a reliable instrument to boost sports performances. Flow is defined and will be detected in accordance with the valence/arousal theory.

The chosen use case refers to athletes involved in low cardio agonistic performance (e.g., golf, archery, racing), as training for these sports is not primarily physical, and mental training is particularly needed. Furthermore, the presence of a very accelerated and stressed cardiac activity could widen interpersonal variability: this, in turn, would lead to difficulties in the learning phases of algorithms for the classification of physiological patterns.

2. State of the Art

Csikszentmihalyi defined Flow as a “holistic sensation that people feel when they act with total involvement” [6] and as a state balanced between boredom and anxiety [1] (or “Beyond boredom and anxiety”, as the book with its first description titles [6]). The first formulation of the construct of flow puts the main focus on the possibility of reaching an intrinsic enjoyment of the experience when the challenge of the activity meets the level of skills of the person. Play and autotelic activities, which are perceived as intrinsically rewarding, are natural examples, but findings in these fields suggest the possibility to shift this kind of experience to less enjoyable tasks [6]. Variations in the quality of personal experience are tracked through the experience sampling methods (ESM), consisting of repeated assessments of the subject’s status and activities timed according to a signaling device. This analysis represents a reliable methodology in different contexts outside the laboratory but can be intrusive, interrupting the activity, or disrupting the performance [7].

Further theorizations followed observations about interpersonal differences in the experience and in the predisposition to flow: autotelic personalities are more prone to experience flow [1], which shows to be not just a momentary state but a trait of the person [8]. Furthermore, flow appears to be a multidimensional experience, including, for Csikszentmihalyi [1], these nine dimensions [2]:

- Challenge-Skill Balance
- Action-Awareness Merging
- Clear Goals
- Unambiguous Feedback
- Concentration on Task at Hand

- Sense of Control
- Loss of Self-Consciousness Concern
- Transformation of Time
- Autotelic Experience

Major interest in flow arose in sports psychology with the change of paradigms due to the emergence of positive psychology: the focus moved from the aim of removing negative thoughts and anxieties to improving the physical and mental abilities of an athlete focusing on aspects like motivation and flow [5].

To evaluate all the aspects related to the definition of flow and to create a methodology not interrupting the performance and reliable in a sports context, Jackson et al. proposed the Flow State Scale (FSS) [2], and the Dispositional Flow Scale (DFS) [9]. FSS focuses on a specific performance event [2], and evaluates flow as a state, while DFS is focused on a wider personal disposition to flow [9] and analyzes flow as a trait [8]. FSS-2 and DFS-2 were deployed with further revisions [10] and translations in different languages are available (e.g., Italian [11], French [12], Spanish [13], and Japanese [14]).

These models of analysis are more ecological, they profile the subject both in state and trait aspects and do not interrupt the performance. Despite this, they still do not manage to return a flow value right when it is happening. Analysis of biomarkers extracted from the psychophysiological activation of the subject is already applied to other emotive states: their use in the detection of flow appears therefore a viable strategy.

Russell's theory of the Circumplex Model of Affect classifies the whole spectrum of emotions distributing them in a cartesian space created around two perpendicular axes: pleasantness and activation, placing emotions such as excitement, relaxation, depression, and distress at the four extremities (e.g., excitement: high pleasantness and high activation, depression: low pleasantness and low activation) [15]. Likewise, Lang organizes emotion around the axes of affective valence and arousal [16] according to his Self Assessment Manikin, designed to graphically measure the level of perceived internal valence, arousal, and dominance [17]. Flow was charted in similar bipartite models by Massimini et al. [18] and Delle Fave [19], in a challenges and skills model, with Flow representing high challenges and high skills, and by Berger, in a personal experience and performance model, with Flow representing high experience and high performance [20]. Berger's model was then implemented by Diana, applying the theory specifically to the sports context [5].

Arousal and valence models are implemented in numerous studies aiming to classify emotions via physiological recordings, with positive findings around the use of peripheral physiological signals. Skin conductance and EMG proved to be reliable indicators of arousal, while ECG components, such as HR and HRV, and respiration are good indicators for valence [20,21]. Special attention is devoted to the EEG activity: arousal is found to be influenced by slow alpha, alpha, and theta bands activity [22], especially with negative correlations with theta, alpha, and gamma bands. Specifically, overall arousal seems inversely related to alpha, while central alpha correlates negatively with higher arousal [21,23]. Increasing arousal shows positive correlations with alpha power in frontal areas and delta bands in right posterior areas [24]. Valence influences are found in beta and gamma bands [22], with a direct correlation with the power of theta and alpha and effects in all the frequency bands [21,23]. An increase in positive valence is reported to correlate negatively with theta power in frontal areas, and asymmetry in power in the lower alpha bands correlates with self-reported valence [24]. Focal positions in the International 10–20 system appear to be Fpz for arousal and F3 and F4 for valence [25].

The physiology of flow is studied in correlation with EMG activations, where muscular activation is connected to results in questionnaires on flow perception [26] and EEG power and patterns of frequency bands. EEG data appear to be more reliable data in detecting flow than peripheral biosignals, [27] and findings correlate flow with the beta band [26]. Corticomuscular coherence (CMC), which correlates EEG (especially beta and gamma bands) and EMG activations, seems also a valid indicator to study flow [26]. Studies on the neural correlates of flow showed that changes in brain activity were linked to individual flow experiences and different flow propensities. In addition, the flow was linked positively to the putamen and inferior frontal gyrus activity and negatively to the amygdala and medial prefrontal cortex activity [28].

The interest that the field of computer science has begun to devote to human emotions has given birth to new opportunities for development and overcoming problems of lack of consistency in results when analyzing physiological data just with classical statistics [29,30]. Affective Computing is a rising domain defined by Picard as “computing that relates to, arises from, or deliberately influences emotions” [31,32]. One of its primary goals is to use AI to create an Affective System capable of understanding human emotion through expressions, gestures, voice intonation, and, most importantly, biosignals [32]. Machine Learning (ML) in particular, as a branch of Artificial Intelligence, is found to be a suitable instrument to analyze physiological activity to both recognize specific emotions and evaluate valence and arousal levels.

Machine Learning is typically implemented after data are gathered from biosensors, while the experimental subjects are presented with tasks, which elicit the emotion or specific levels of arousal and valence. These moments are then labeled and used to populate a database, which will train a supervised ML model, through a classification, if the needed results are classes; through a regression, if the results will be linearly distributed [33].

Affective computer applications open also to the ability to merge different biosignals to discriminate further multiple complex emotions. For example, in Picard et al. (2001) neutral feeling, anger, grief, joy, reverence, hate, platonic love, and romantic love were classified with 81% of accuracy, especially thanks to features of HR, skin conductance, and respiration [34]. Arousal and valence were shown, for example, to be better discerned with merged data from EEG and eye gaze movements, than from EEG, eye gaze, GRS, ECG, respiration pattern, or skin temperature alone [35]. ML potentialities increase also the possibility to reach significant results with low cost and less invasive sensors, as in Girardi et al. (2017), where EEG and skin conductance data together show the best performance [33].

Regarding the performances of the algorithms in arousal and valence classification, literature reports a wide utilization of Deep Neural Networks learning frameworks [36] and Support Vector Machine (SVM) [22,27,33,35,36,37,38,39]. The use of Linear Discriminant Analysis [20,27], Naive Bayes [23,39], Quadratic Discriminant Analysis (QDA) [27], Logistic Regression [36], K-nearest neighbors (KNN) [36,39], Decision Tree [40], J48 [40], and Random Forest [39] is also reported.

Few studies also analyzed arousal and valence levels in realtime, without a specific focus on flow, for example on EEG [37] and ECG patterns [38]. Muller et al. (2015) detect different emotions in developers in real-time, during their daily tasks, focusing also on flow: the subjects' physiological activity was recorded, and their emotions were assessed every five minutes, through a questionnaire. However, the creation of the database was performed by segmenting data just by task and the elaborated data were available only posthoc [40]. Rissler et al. (2020) aim to detect, specifically, different intensities of flow (high or low), in real-time and in the field, in a work environment, with a ML approach based on the analysis of Heart Rate Variability (HRV) features. Also in this study, the time stream is segmented by task (e.g., 300 seconds) and data processing is performed after the recording [39].

The aim of reporting flow while it happens may be linked to studies on interruptibility. In Züger et al. (2017), the objective is the creation of an interface in a work environment, able to signal to colleagues (with information from one's computer activity), when a person is in flow and does not want to be interrupted [41].

3. Methodology

Physiological activation results in an appropriate indicator of emotive and psychological status, including Flow. Specifically, difficulties affected the design of experimental tests for elicitation of Flow, which needed tailoring to the subject [27]. The possibility of mapping Flow in a valence/arousal model as a high valence and high arousal indicator seems indeed actable and in accordance with the literature. Fig. 1 illustrates the proposed configuration, merging Lang's valence and arousal formulation [16] with models including flow as Delle Fave's, Berger's, and Diana's [18,19,5].

It is to be noted that high arousal and high valence conditions can be related to different positive and activating states, such as joy or excitement [16]. For example, flow and happiness, are strongly correlated even in the first Csikszentmihalyi works [1].

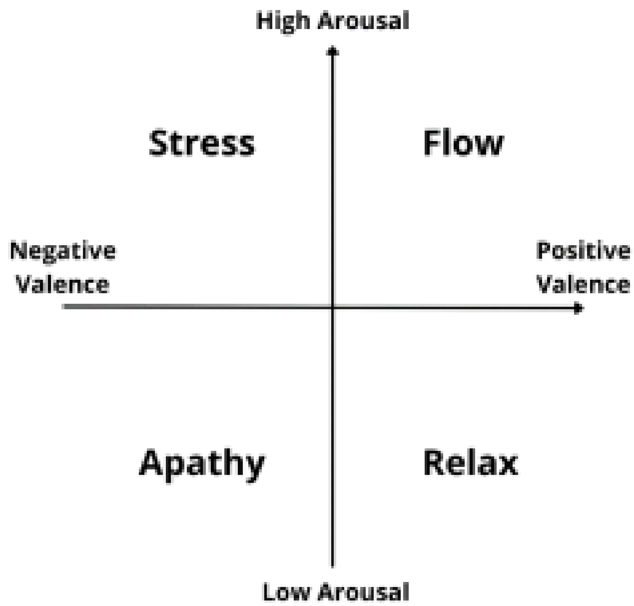

Fig. 1. Flow inserted in an arousal and valence model

In his following works [6] the attention to further characteristics of the flow, such as emotional, situational, motivational, and cognitive [22], leads to separating and distinguishing it from other positive emotional states.

To further discriminate Flow from other states, we propose to complement the classical affective computing arousal valence modality by assessing also the perceived level of challenge of the task and personal skills. Among the dimensions characterizing Flow, the challenge-skill balance is considered the more meaningful [18,23,24,25]; as in the quadrant described in Massimini et al. (1988) and Delle Fave et al. (2011), flow represents the high skills and high challenge state, in opposition to anxiety, boredom, and apathy states [18,19]. Since the levels of arousal, valence, challenge, and skill are subjective assessments, we intend to integrate, as objective dimension, the level of attention of the subject to the task.

ML results in a powerful system to perform physiological analysis, but previous studies mostly focus on post-hoc processing and long-time frames. A ML model capable of a realtime elaboration of valence and arousal levels, with the aim of returning an indication of the Flow moment, is defined in this work. The proposed logic is also scalable on time, depending on the available computing power and the need for accuracy from the physiological point of view. A description of the experimental steps is provided hereafter.

2.1 Preliminary analysis of databases

An explorative ML approach will be conducted by exploiting multimodal databases, available for free for scientific purposes, such as DEAP [21], MAHNOB [26], and DECAF [27], where multiple physiological registrations are linked to valence and arousal levels of the participants. As declared inclusion criteria, subjects were healthy, with different cultural and educational histories, and gender-balanced [21,26,27]. The aim of this phase is the creation of a supervised learning algorithm able to predict levels of valence and arousal from physiological recordings. A successive feature selection will be implemented to sort the significance of specific physiological signals and their subfeatures. The chosen databases will be merged, creating a new balanced dataset; a selection of classification and regression algorithms will be validated, through both 10-fold and leave-one-out cross-validations, and tested. Different models will be additionally created in order to analyze different temporal spans (e.g., entire recording, 1 min, 30 sec, 10 sec), which will be considered both independently and maintaining their sequential linearity.

2.2 Preliminary Study

A within-subjects study design will be planned, and conditions able to elicit different levels of arousal and valence will be delineated to be presented to the participants while recording their physiological data. The authorization of the ethics committee will be requested. Around 25/30 subjects will be enrolled (based on the numerosity of the sample of DEAP [21], MAHNOB [26], and DECAF [27] databases), screened for the exclusion of disorders or pathologies which could influence physiological data, as psychiatric disorders, or cardiac dysfunctions. Inclusion criteria will follow the inclusion criteria of the selected databases: healthy subjects, with different cultural and educational histories, and gender balanced will be enrolled.

New physiological data will be recorded: biosignals and their specific features (e.g., HRV detailed components) will be selected according to the findings of the preliminary analysis. Gold standard instrumentation will be selected; the 32-channel EEG Brain Vision actiCHamp, or similar, with 512 HZ of sampling or more will be employed for EEG recording. ProComp Infiniti with a 256 Hz sampling rate will be employed for peripheral signals like ECG, Skin Conductance, tip-finger Temperature, Respiration, and facial EMG (on zygomaticus major, orbicularis oculi, and corrugator supercilii). Participants will complete questionnaires about demographics and their personal flow characteristics will be assessed through the Flow State Scale-2 and the Dispositional Flow Scale-2. Their valence and arousal level will be assessed after each trial, using the Self Assessment Manikin (SAM) proposed by

Lang [16], used in the 9-point version. SAM consists of 5 stylized mannequins creating a 5-point Likert scale, representing a growing level of valence and a growing level of arousal; a more detailed valuation can be reached by adding points between the Manikins as in Mehrabian et al. (1974) [28] creating a 9-point Likert scale [29]. Challenge and skill levels of the subjects will be evaluated via three further 9-point Likert scales as in Engeser et al. (2008): "Compared to all other activities which I partake in, this one is…" (easy/difficult), "I think that my competence in this area is… (low/high), "For me personally, the current demands are..." (too low/just right/too high) [25]. The attention on the task will be assessed via the analysis of the eye-gaze movements [30–32], using eye-tracking.

Subjects will be exposed to situations that would elicit high and low combinations of valence and arousal, as to a baseline recording, to set the “ground truth”. Specific focus will be required in designing trials which would permit flow elicitation. Previous studies suggest, for instance, listening to music selected by the participant [33], watching video clips [21], playing video games [34], using social media [35], or performing mental arithmetic tasks [36]. Test phases will be randomized to prevent order or sequence effects. The implementation of a video game with different levels, seems a viable methodology to present the subjects with comparable tasks, which could enhance either boredom (too easy level), anxiety (too hard level), or a condition balanced with the subject's abilities [25,34,37]. Moreover, the choice of a video game with multiple levels will allow a more specific alignment with the capabilities of the individual participant [34].

2.3 Database and Machine Learning Model Construction

Data collected in the preliminary study will populate a new database and be labeled following the subject's Self-Assessment Manikin (SAM) with a 9-point scale and the supposed emotional state elicited during each experimental situation. The minimum dataset will be selected following the literature and the results from the previous phase, to reduce computational costs. Recordings will be divided into different time epochs, as in the entire experimental class, 1 min, 30 sec, and 10 sec; each different time sampling will be analyzed separately, and each time epoch will be considered both independently and maintaining their sequence linearity.

Following the preliminary analysis results, transfer learning techniques will be applied to the best performing algorithms: the inclusion and exclusion criteria will be the more similar possible between the first two phases. Nevertheless, transfer learning will permit to adapt learning model also on slightly different kinds of data. It will be applied in supervised learning classification and regression models, along with the implementation of new training models. Data will be validated through both 10-fold and leave-one-out cross-validations and tested both with hold-out data and with data extracted from the database of the preliminary phase, in line with previous research [33,38,39].

From the algorithm results, through feature analysis, the most viable biosignals and their sub-features will be selected; particular attention would be also paid to cost-effectiveness criteria and the accessibility and existence of wearable systems. Prediction models will be compared and evaluated in terms of precision, accuracy, computational costs, and time, selecting those with the best time/performance ratios.

A further step will be the creation of a python-based application to run the best performer algorithm in real-time while receiving the selected biosignals from the subject, divided into the best functional predetermined epochs. Specific feedback will also signal valence and arousal levels, especially in situations with high arousal and high valence.

4. Discussion

The expected results of this prospective can be summarized in the following points:

- development of a ML model able to predict high arousal+high valence moments in selected public databases;
- construction of a multimodal database of physiological recording, including biosignals components and features, related to tasks evaluated by valence and arousal;
- validation of experimental stimuli able to elicit different levels of valence and arousal; possibility to record proxies of flow status through high valence and high arousal tasks;
- development of a ML model able to predict different levels of valence and arousal;
- minimal and more economical valid measure to make the person, the experimenter, and the coach aware of flow status (high valence and high arousal);
- development of a model to record flow in real-time, through the minimum time delta needed to recognize valence and arousal level, especially high valence and high arousal.

5. Conclusion

A prospective approach for the construction of a ML model capable of detecting levels of arousal and valence in real-time with a special focus on high valence and high arousal conditions, associated with flow, is described in this work. This aim will be reached in a 4-steps design:

1) a preliminary ML analysis performed on databases of physiological activations recorded during tasks, evaluated per valence and arousal levels;

2) specific tasks for the elicitation of different levels of arousal and valence will be designed and tested on subjects while recording their physiological data and their reaction to the task (on valence/arousal scales);

3) the creation of a database populated with the physiological activation recordings labeled according to arousal and valence levels, and segmented in different time epochs;

4) a ML model able to classify different levels of arousal and valence, to find the minimal and more economical (both in terms of sensors and time) amount of data to predict a flow status.

The creation of a system that detects the flow status from biosignals seems a reachable objective thanks to ML. This instrument would help to create new instruments to assess flow in an accurate and reliable way, which is reported to be "one of the greatest challenges in flow research" [40,41]. Moreover, while in much research the state of flow is considered elusive and infrequent [42], studies on elite-level athletes describe flow as a more controllable event, both in duration and quantity [41]. In this view, a system that detects flow can be used to report when athletes are not in flow, to enable them to implement proper strategies to reach it.

Besides, being aware of the presence of flow may allow the use of specific techniques for prolonging it [43]. Finally, having the knowledge of the situations, antecedents, and effects linked to a specific flow moment would facilitate, in a second moment, the replication of the same conditions, having intuitions about causal dynamics, allowing to better focus their strategies, and to evaluate the utilized treatments. We also hypothesize that the increase in one's level of introspection and abilities to reach the flow will rise the possibility of improving athletes' performance and their perceived level of well-being. Few or no research deeply investigates the relationship between awareness of being in flow and its improvement: we hope that our system would allow for further investigations.

Further development will follow the final findings: a use case will be defined and tested, both in a laboratory and in a real-life setting, to evaluate the potential of obtained algorithms and to construct a feedback application, able to interact with wearable sensors. This final device may also be utilized in different domains, such as work performance or different kinds of sports: arrangements will be needed to implement such a device also in sports which stimulate high cardiac and physiological activity.

DECLARATIONS

Author contributions

ES designed and planned the study with the support of AB and GR. ES wrote the first draft of the manuscript and then AB, NN, and GR contributed to the final version, supervising the description of the parts of the manuscript, as well as the rationale and the scientific contributions. All authors read and approved the final manuscript.

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