On the Need of New Methods to Mine Electrodermal Activity in Emotion-Centered Studies

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Abstract. Monitoring the electrodermal activity is increasingly accomplished in agent-based experimental settings as the skin is believed to be the only organ to react only to the sympathetic nervous system. This physiological signal has the potential to reveal paths that lead to excitement, attention, arousal and anxiety. However, electrodermal analysis has been driven by simple feature-extraction, instead of using expressive models that consider a more flexible behavior of the signal for improved emotion recognition. This paper proposes a novel approach centered on sequential patterns to classify the signal into a set of key emotional states. The approach combines SAX for pre-processing the signal and hidden Markov models. This approach was tested over a collected sample of signals using Affectiva-QSensor. An extensive human-to-human and human-to-robot experimental setting is under development for further validation and characterization of emotion-centered patterns.

1 Introduction

Wrist-worn biometric sensors can be used to track excitement, engagement and stress by measuring emotional arousal via skin conductance (SC), a form of electrodermal activity (EDA). Understanding EDA enables us to understand the role of the sympathetic nervous system in human emotions and cognition.

Although of critical value to neuroscience and psychophysiology, the study of EDA had been limited to the combined analysis of basic features: SC level, SC response amplitude, rate, rising time and recovery time. This method has a clear drawback – the discarding of flexible elicited behavior. For instance, a rising or recovering behavior may be described by specific motifs sensitive to sub-peaks or displaying a logarithmic decaying. This weak-differentiation among different stimuli response have led to poor emotional mappings, with EDA being mainly used just for the purpose of defining the intensity-axis of an emotional response.

This paper proposes a novel paradigm for the EDA analysis, the application of a sequence classifier over a symbolic approximation of the signal. This has the promise of disclosing emotions in real-time. In this way, scientific and clinical researchers can make dynamic adjustments to their protocols. Therapists

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can gauge the effectiveness of in-session treatments. Professors can adapt their teaching strategies according to each students' response. Marketers can closely monitor focus-groups. Every person can use it to unfold unconscious behavior.

This paper is structured as follows. *Section 2* reviews the state-of-the-art on EDA and emotions theory in the context of biometric sensors. *Section 3* identifies the target problem. *Section 4* describes the proposed approach. *Section 5* proposes an experimental setting for the discovery of EDA emotion-driven patterns. *Section 6* identifies potential applications.

2 Related Research

This section provides a synthesized overview of the key contributions related to emotion recognition using physiological signals in general and EDA in particular.

2.1 Emotion Recognition Using Physiological Signals

Measuring physiological signals is increasingly necessary to derive accurate analysis from emotion-driven experiments. Physiological signals can surpass social masking and high context-sensitivity of image and audio analysis, track emotional changes that are less obvious to perceive, and provide complementary paths for their recognition (both cognitive and sensitive). However, their subtle, complex and subjective physical manifestation plus their idiosyncratic and variable expression within and among individuals present relevant key challenges.

The common problem in this context is to define a statistical learning method that can provide stable and successful emotional recognition performance. The main implication is to gain access to someone's feelings, which can provide important applications for human-computer interaction, conflict reduction, clinical research, well-being (augmented communication, self-awareness, therapy, relaxation) and education. Table 1 introduces a framework of five key questions to answer this problem. Good surveys with contributions gathered according to the majority of these axes include [15][38].

2.2 Emotions and the Electrodermal Activity

Electrodermal activity (EDA) is an electrical change[1] in the skin that varies with the activation of the *sympathetic* nervous system[2], which is responsible to activate positive excitement and anticipation, and to mobilize the body's fight-or-flight response by mediating the neuronal and hormonal stress response [1]. Electrical changes in the skin are a result of an increased emotional arousal or cognitive workload[3] that leads to an intense physical exertion, where brain

[1] The use of endosomatic methods is not target.

[2] Part of the autonomic nervous system responsible for the regulation of homeostatic mechanisms that require quick responses, complementary to "rest-and-digest" mechanisms triggered by the parasympathetic division.

[3] Involved neural pathways are numerous since excitatory and inhibitory influences on the sympathetic nervous system are distributed in various parts of the brain.

Table 1. The five decision-axes for recognizing emotions over physiological signals

Which physiological signals to measure?	Although EDA is the signal under analysis, its use can be complemented with other signals as, for instance, respiratory volume and rate if the goal is to recognize negative-valenced emotions, or heat contractile activity to distinguish among positve-valenced emotions [39]. Depending on the target emotions to assess, a combination of different modalities is desirable [15]. The key challenge is that modalities of emotion expression are broad (including electroencephalography; cardiovascular activity through electrocardiography, heart rate variability, cardiac output or blood pressure; respiratory activity; and muscular activity using electromyography), some yet being inaccessible or less studied (as blood chemistry, neurotransmitters and brain activity) and many others being too non-differentiated [29];
Which approach to follow?	User dependency, stimuli subjectivity and analysis time are the key axes [35][37]. In user-dependent approaches labeled EDA signals are vastly collected per user and the classification task for a target user is based on his historic pairs. User-independent approaches collect and use the pairs from a diversity of individuals to recognize emotions. Contrasting to "high-agreement" studies, in subjective experiments, the user is requested to self-report and/or to produce via mental imagery his response to a stimuli. Finally, the mining of a signal can be done statically or dynamically. This work targets the user-independent, non-subjective and dynamic evaluation quadrant;
Which models of emotions select?	The most applied models are the *discrete* model [13] centered on five-to-eight categories of emotions (there is considerable agreement in using happiness, sadness, surprise, anger, disgust, fear [15]) and the *dimensional* valence-arousal model [18] where emotions are described according to a pleasantness and intensity matrix. Other less commonly adopted models include the Ellsworth's dimensions and agency [27], Weiner's attributions and recent work (at MIT) focused on recognizing states that are a complex mix of emotions ("the state of finding annoying usability problems") [29];
Which experimental conditions to adopt?	The selected stimulus should evoke similar emotional reactions across individuals, be non-prone to contextual variations (time to neutralize the emotional state and to remove the stress associated with the experimental expectations), capture states of high and low arousal and valence to normalize the features, avoid multiple exposures (to not desensitize the subject), and provide reliable and reproducible methods according to existing guidelines [6][28]. The undertaken experiment is defined in section 5;
Which data processing and mining techniques to adopt?	Four steps are commonly adopted [15][6]. *First*, raw signals are pre-processes to remove contaminations (noise, external interferences and artefacts). Methodologies include segmentation; discard of initial and end signal bands; smoothing filters; low-pass filters such as Adaptive, Elliptic or Butterworth; baseline subtraction (to consider relative behavior); normalization; and discretization techniques [28][31][16][10]. *Second*, features are extracted. These features are statistical (mean, standard deviation), temporal (rise and recovery time), frequency-related and temporal-frequent (geometric analysis, multiscale sample entropy, sub-band spectra) [14]. The number may vary between a dozen to hundreds of features depending on the number and type of the adopted signals [15]. Methodos include rectangular tonic-phasic windows; moving and sliding features (as moving and sliding mean and median); transformations (Fourier, wavelet, empirical, Hilbert, singular-spectrum); principal, independent and linear component analysis; projection pursuit; nonlinear auto-associative networks; multidimensional scaling; and self-organizing maps [14][19][15]. *Third*, features that might not have significant correlation with the emotion under assessment are removed. This increases the classifiers' performance by reducing noise, enabling better space separation, and improving time and memory efficiency. Methods include: sequential forward/backward selection, sequential floating search, "plus t-take-away r" selection, branch-and-bound search, best individual features, principal component analysis, Fisher projection, classifiers (as decision tress, random forests, bayesian networks), Davies-Bouldin index, and analysis of variance methods [15][6]. *Finally*, a classifier is learned using the previously selected features. Methods include a wide-variety of deterministic and probabilistic classifiers, with the most common including: k-nearest neighbours, regression trees, random forests, Bayesian networks, support vector machines, canonical correlation analysis, neural networks, linear discriminant analysis, and Marquardt-back propagation [24][15][25].

stimulus may lead to sweating[4]. The skin is believed to be the only organ to react only to the sympathetic part of the nervous system, allowing its measurements to get a more accurate reading [8].

By monitoring EDA is possible to detect periods of excitement, stress, interest and attention. However, heightened skin conductance is also related with engagement, hurting, intrigue, distress and anticipation ("the unknown behind the wall") [1]. In fact, EDA is influenced primarily by the activation of an inhibition function that is involved in responding to punishment, passive avoidance or frustrative non-reward, which are different forms of anxiety [8]. These recent clarifications on the role of EDA responses, require careful experimental conditions and, as target by this paper, more robust methods for their mining.

On one hand, measuring EDA has clear advantages: sympathetic-centered response, neuro-anatomical simplicity, trial-by-trial visibility, utility as a general arousal and attention indicator, significance of individual differences (reliably associated with psychopathological states), and its simple discrimination after a single presentation of a stimulus. On the other hand, EDA has a relatively slow-moving response (latency of the elicited response and tonic shifts between 1 and 3s and varying among individuals [8]), requires lengthy warm-up periods, and has multiple influences that may be either related with the subject attention and personal significance, stimuli activation, and affective intensity.

The variety of electrodermal phenomena can be understood by mining changes in tonic SC level (SCL) and phasic SC response (SCR), related to tonic or phasic sympathetic activation. Researchers have found that tonic EDA is useful to investigate general states of arousal and alertness, while phasic EDA is useful to study multifaceted attentional processes (related to novelty, intensity, and significance), as well as individual differences in both the normal and abnormal spectrum [8]. Although these are important achievements, there is still the need to verify if, under controlled experimental conditions, the inclusion of advanced signal behavior can increase or not the accuracy of a target classifier.

Experimental Evidence. Historical EDA studies had been focused on learning efficiency, response speed and, as target by this paper, emotional appraisal. Three distinct types of experiments have been done.

First: experiments using discrete stimuli. Experiments with brief and isolated stimuli, include the study of: *innocence* using the guilty knowledge test [22]; *familiarity* by distinguishing between meaningful and unfamiliar stimuli [1]; *relevance* through non-balanced occurrence of a stimuli category or through elicitation of priorities [2]; *affective valence* (although not good in discriminating along the positive-negative axis, EDA was, for instance, found to be higher for erotic pictures or striking snakes than for beautiful flowers or tombstones [17]); and *planning and decision-making* processes via the "somatic marker" hypothesis [34]. Backward masking is often used to prevent awareness of conditioning stimulus by preventing its conscious recognition [8]. The great challenge when

[4] EDA has both a functioning role (maintain body warmth, and priming the body for action) and evolutionary meaning (protection from grasping injury).

recognizing emotion is that the elicit response are considered to be part of the orienting response to novel stimuli, which influence should be removed.

Second: experiments using continuous stimuli. When studying effects of long-lasting stimuli, SCL and frequency of spontaneous SCRs (NS-SCRs) are key measures. Experiments include the study of: *strong emotions* reproducing, for instance, genuine states of fear (highest SCLs) and anger (greatest NS-SCRs) [1]; *reappraisal* through authentic, forbidden and awarded emotional display; physical and mental *performance*; *attention* (affecting rising and recovery time in vigilance tasks); and different forms of *social interaction* involving, for instance, *judgment* (NS-SCRs rate inversely related to the judged permissiveness of a questioner), *distress invocation* through the study of relationships, or the *contagious effect* by relating, for instance, heightened autonomic arousal with living with over-involved individuals [8][7]. Energy mobilization seems to be the driver for tasks that either require an effortful allocation of attentional resources or, but not necessarily exclusive, invoke the concepts of stress and affect.

Third: potential long-term experiments targeting personal traits. High NS-SCRs rate and slow SCR habituation are used to define a trait called lability with specific psychophysiological variables [11]. Traits have been defined according to: *information processing* [32], *operational performance*, *brain-side activation* through studies with epileptic individuals or recurring to electrical stimulation (right-side of limbic structures stimulation increases more SCR than the left) [1], *sleeping patterns* [21], *age* [8], *psychopathology* (mainly diagnosable schizophrenia and subjects with tendency to emotional withdrawal and conceptual disorganization, with different traits regarding to the *SCR conditioning* (revealing paths to emotional detachment as absence of remorse and antisocial behavior as pathological lying and substance abuse), *tonic arousal*, and *response to mild innocuous tones* [23]. These results suggest that hypo- or hyper-reactivity to the environment may interfere with fragile cognitive processing in ways that underline vulnerabilities in the areas of social competence and coping.

Approaches to Analyze EDA. Current approaches are focused on features' extraction from the signal, neglecting its motifs. When measuring EDA from discrete stimuli, the key adopted feature is the SCR amplitude. The response latency, rise time and half recovery time are sporadically adopted, although their relation to psychophysiological processes remain yet unclear.

When studying prolonged stimulation, both specific and spontaneous responses are considered. NS-SCRs frequency is the feature of interest, which can be easily computed using a minimum amplitude as threshold. An alternative is to compute the SCL, which can either include or exclude the specific responses periods depending on the experimental conditions (continuous or sporadic stimuli presentation). For the latter case, a latency window criterion is required.

Finally, the analysis of traits also recurs to NS-SCRs rate, SCL, response amplitude and habituation. The challenge is on whether to use or not a range correction, by capturing the maximum and minimum EDA values during a session. Both relative and absolute approaches can be found in the literature, with pros-and-cons [8] and alternatives [3]. Test-retest reliability, psychometric principles and questionnaires are crucial to view EDA response as a trait [8].

3 The Problem

The target problem of this work is to generalize the EDA sequential behavior for different emotions and to assess their effect in emotion classification accuracy. In particular, for emotions elicited in human-robot vs. human-human interaction. Emotion-driven EDA behavior can be learned by statistical models to dynamically classify emotions. The contribution of this work is on proposing a novel approach for this problem centered on an expressive pre-processing step followed by the direct application of a sequence classifier, instead of performing traditional methods of feature-driven analysis. Initial evidence for the good performance of this approach over a preliminary collection is presented.

4 The Proposed Approach

This section proposes a new paradigm for emotion-recognition from EDA, collapsing the traditional four-step process into a simpler and more flexible two-stage process. There are two core strategies: to rely upon a good representation of the signal, and to mine sequential patterns instead of retrieving domain features.

4.1 Experimental Conditions and Data Properties

The collected EDA signals were obtained using wrist-worn Affectiva-QSensors[5] and closely-controlled experimental procedures[6]. The wireless connectivity of the adopted sensors enables the real-time classification of emotional states.

Additionally, the following signals were collected using Affectiva technology: facial expression series, skin temperature and three-directional motion. Although this paper is centered on the analysis of EDA, the joint analysis of the adopted signals (multivariate time series mining) is of additional interest and can be done by extending the dynamic Bayesian networks. Currently, the last two signals are being currently used to affect the EDA signal: skin temperature to weight SCL by correcting the individual reaction to room temperature, and body intense movements to smooth correlated EDA variations. Facial recognition is adopted just for post-experimental validation and interpretation.

[5] Data captured is considered as reliable as the tethered system developed by BIOPAC, often used in physiological research, and is currently being adopted over a hundred universities, which enable a standardized way of comparing experiments.

[6] Includes measuring of very high and low states of EDA, conservative signal stabilization criteria, standardized stimuli presentation and context reproducibility.

4.2 Processing the Signal Using SAX

Since our goal is sequential data classification, we are interested in one approach that simultaneous supports: *i)* reduced dimensionality and numerosity, and *ii)* lower-bounding by transforming real-valued EDA into a symbolic representation. First, reducing the high dimensionality and numerosity of signals is critical because all non-trivial data mining and indexing algorithms degrade exponentially with dimensionality. Second, symbolic representations allow for the application of more expressive techniques like hidden Markov models and suffix trees.

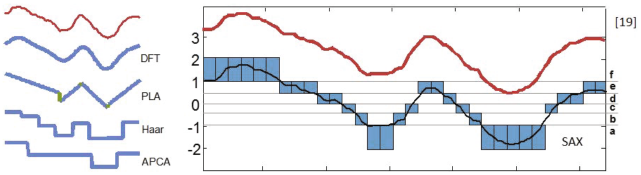

Fig. 1. Commonly adopted representations vs. SAX [20]

While many symbolic representations of time series exist, they suffer from two critical flaws: *i)* mining algorithms scale poorly as the dimensionality of the symbolic representation is not changed, and *ii)* most of these approaches require one to have access to all the data, before creating the symbolic representation. This last feature explicitly thwarts efforts to use the representations with streaming methods, required for a dynamic emotion recognition from EDA. To the best of our knowledge only Symbolic ApproXimation (SAX) provides a method for performing operations in the symbolic space while providing the lower bounding guarantee [20][33]. SAX is demonstrated to be as competitive or superior as alternative representations for time series classification. SAX allows a time series of arbitrary length n to be reduced to a string of w-length ($w<n$, typically $w \ll n$) with dimension or alphabet size $d>2 \in \mathbb{N}$. To mine signals in main memory for real-time classification purpose, w and d parameters have to be carefully chosen. Fig.1 compares SAX with the four most common adopted alternatives [12]. A raw time series of length 128 is transformed into the word ffffffeeeddcbaabceedcbaaaaacddee.

This work implemented SAX in two steps. Firstly, the signal is transformed into a Piecewise Aggregate Approximated (PAA) representation, which provide a well-documented method to reduce dimensionality. Secondly, the PAA signal is symbolized into a discrete string allowing lower bounding, which can be useful to perform distance metrics for recognizing emotion-centered patterns needed for the classification task. Here, an important technique with visible impact in accuracy, is the use of a Gaussian distribution over the normalized signals to produce symbols with equiprobability recurring to statistical breakpoints [20]. In Fig.1, breakpoints define the boundary criteria across symbols.

Different criteria may be adopted to fix the signal dimensionality and numerosity values. The normalization step can be done with respect to all stimulus, to a target stimuli, to all subjects and to the available responses of a target subject. Additionally, two mutually-exclusive strategies can be defined to deal with variable signal numerosity. First, a ratio to reduce numerosity can be uniformly applied across the collected signals. Second, piecewise aggregation can be adopted to balance the signals numerosity with respect to a particular emotion label. Note that since the temporal axis is no longer absolute, relevant information is lost and, therefore, this second strategy should only be adopted when complemented by the first.

4.3 Mining the Signal Using Hidden Markov Models

After a pre-processing step using SAX and simple artefact-removal techniques, there is the need to apply a mining method over sequential data to categorize the behavior presented for different emotional states. This has the promise of increasing the accuracy as a probabilistic sequence generation can be learned from the raw processed signal for each emotion-class, instead of loosing key behavioral data through the computation of a simple set of metrics. Some of the most popular techniques include recurrent neural networks, dynamic Bayes networks and adapted prototype-extraction [5][26].

This paper proposes the use of hidden Markov models (HMM), a specific type of a dynamic Bayes network, due to their stability, documented performance in healthcare domains, simplicity and flexible parameter-control [30]. In particular, [4] proposes that, at least within the paradigm offered by statistical pattern classification, there is no general theoretical limit to HMMs performance given enough hidden states, rich enough observation distributions, sufficient training data, adequate computation, and appropriate training methods.

Markov models simplicity derives from the assumption that future predictions are independent of all but the most recent observations. In a HMM, an underlying and hidden automaton of discrete states follows a Markov constraint and the probability distribution of the observed signal state at any time is determined only by the current hidden state. Given a set of training signals labeled with a specific emotion, the core task is to learn the transition and generation probabilities of the hidden automaton per emotion. This is done in practice by maximizing the likelihood function iterations of an efficient forward-backward algorithm until the transition and generation probabilities converge [30][5]. Finally, given a non-labeled signal, the selection of the emotion can be naively classified by evaluating the generation probability of the exponential paths generated from each learned automaton lattices, and by selecting the path having the highest probability. For this purpose, the Viterbi algorithm was selected [36].

In order to define the input parameters for the HMMs two strategies may be consider. First, a sensitivity-analysis over the training instances per emotion to maximize accuracy. Second, parameter-definition based on the signal properties (e.g. high numerosity leads to an increased number of hidden states). Additionally, an extension to traditional HMMs can be made to deal with multiple

EDA signals with varying dimensionality (smoothed and pronounced EDA). This aims to increase the accuracy of the target approach by providing multiple paths to select the label, since one path may not be the best for two different emotions. Currently, this is done by computing the joint probability of the different paths.

5 Validation of Our Approach

The proposed EDA mining approach were applied over a small set of subjects with preliminary but interesting conclusions. This section reviews them and characterizes the experimental setting to be adopted for further validation and emotion-driven EDA characterization.

5.1 Preliminary Results

Preliminary evidence of the utility is described in Table 2. Due to the small sized of the collected sample of stimuli-response EDA, no quantitative analysis on the accuracy, specificity and sensitivity classification metrics is provided.

5.2 Next Steps

To gain further insight of the EDA response pattern to specific emotion-oriented stimuli, we are undertaking a tightly-controlled lab-experiment. We expect to have around fifty subjects and, at least, forty skin-conductive subjects with valid collections. Since eight different stimuli (five emotion-centered and two others) will be used per subject, our final dataset will have above three hundred collected signals, with each stimuli having above thirty instantiations, which satisfies the statistical requirements of hidden Markov models.

Additionally, facial recognition, skin temperature, body 3-dimensional motion and video-audio recording will be captured. A survey will be used to categorize individuals according to the Myers-Briggs type indicator and for a complementary context-dependent analysis of the results. The target emotions are empathy, expectation, positive-surprise (unexpected attribution of a significant incremental reward), stress (impossible riddle to solve in a short time to maintain the incremental reward) and frustration (self-responsible loss of the initial and incremental rewards dictated by the agent). The adopted reward for all subjects is one cinema-session ticket-offer. The stimulus will be presented in the same order in every experience and significant time will be provided between two stimulus to minimize influence, although noise propagation across stimuli is a necessary condition in multiple-stimulus experiment. Equivalent scenarios will be used for human-human and human-robot interaction, with subjects being randomly selected to attend one scenario. The robots used for this experience will be EMYS and NAO[7].

[7] http://emys.lirec.ict.pwr.wroc.pl and http://www.aldebaran-robotics.com

Table 2. Initial observations of the target approach over EDA samples

Challenge	Observations
Expressive behavior	An intricate observation was the sensitivity of the learned HMMs to expressive behavior as peak-sustaining values (e.g. as a response to warm hugs) and fluctuations (e.g. for elicited anger). Such behavior is hardly measured by feature-extraction methods since they loose substantial amounts of potential relevant information during the computation process and are strongly dependent on directive thresholds (e.g. peak amplitude to compute frequency measures). We expect that, with the increase of available signals, HMMs are able to learn internal transitions that capture smoothed shapes per emotion, which enable the discrimination of different types of rising and recovering responses following sequential patterns with flexible displays (e.g. exponential, "stairs"-appearance). The number of discrete hidden values is an important variable for this expressivity. In our current implementation, a sensitivity-analysis over the training instances is performed per emotion until maximum accuracy is achieved;
Numerosity differences	Two strategies were adopted to overcome this challenge. First, signals as-is (with their different numerosity) were given as input to HMMs as dynamic Bayesian networks are able deal with this aspect (note, for instance, the robustness of HMM on detecting hand-writing text with different sizes in [5]). Second, the use of piecewise aggregation analysis by SAX can be used to normalize different signals with respect to their numerosity. However, since a good piece of temporal information is lost (as latency, rising and recovery time), this temporal normalization is performed per stimuli with respect to the average length of responses. This second strategy increases significantly the performance of HMMs if the following algorithmic-adaptation is performed: the input signal is mapped into the standard-numerosity of each emotion in order to assess the probability of being generated by each emotion-centered Markov model;
SCL differences	One of the key challenges is to deal with individual differences in terms of SCL and SCRs amplitude under the same emotion. The normalization step in traditional approaches fails to answer this challenge as SCL and response amplitude are not significantly correlated (e.g. high SCL does not mean heightened SC responses). The Gaussian distribution for dimensionality control used by SAX provide a simple method to smooth this problem. Additionally, our implementation supports both absolute and relative criteria to mine EDA signals, with the scaling strategy being done with respect to all stimulus, to the target stimuli, to all subjects or to subject-specific responses;
Lengthy responses	Rising and habituation time provide a poor framework to study lengthy responses as, for instance, response to astounding stimulus (where spontaneous amplitude-varying relapses are present). This expressive behavior can still be considered in lengthy series by increasing the number of hidden states of the target HMM. Our implementation enables a dynamic adaptation of HMM parameters based on the average length of response to each stimuli;
Peak sensitivity	Our approach has the promise of overcoming the limitations of feature-based methods when dealing with fluctuations of varying amplitude and temporal distance (for instance, non-periodic relapses). This is done by controlling dimensionality using SAX. A range of values for dimensionality can be adapted, with two main criteria being adopted to increase the accuracy of our classifiers: mapping the raw signals into low-dimensional signals to capture smoothed behavior (e.g. alphabet size less than 8) and into high-dimensional signals to capture more delineated behavior (e.g. alphabet size above 10). Currently, two HMM are being generated for each of the strategy, with the joint classification probability being computed to label a response. However, in future work, it is expected an adaptation of the adopted HMMs to deal with multiplicity of signals, each one embedding different dimensional criteria;

6 Applications

The main implication of the potential gains in accuracy for recognizing emotions is an improved access to someone's feelings. One key area covered by the recent efforts to integrate data mining and agent interaction [9]. In the target experiment, this has direct application in *human-robot interaction*. Additional applications include: *clinical research* (emotion-centered understanding of addiction, affect dysregulation, alcoholism, anxiety, autism, attention deficit hyper- and hypoactivity, depression, drug reaction, epilepsy, menopause, locked-in syndrome, pain management, phobias and desensitization therapy, psychiatric counseling, schizophrenia, sleep disorders, and sociopathy); *well being* as the study of the effect of relaxation techniques like breathing and meditation; *marketing* to understand the emotions evoked by a message; *conflict reduction* in schools and prisons by early detection of hampering behavior (particularly important with autistics who have particular trouble understanding theirs and others feelings); *education* through the use of real-time emotion-centered feedback from students to escalate behavior and increase motivation; and many others as biofeedback, EDA-responsive games and self-awareness enhancement.

7 Conclusion

This work introduces a novel paradigm to analyze electrodermal activity in emotion-centered experiments. For this purpose, it proposes an approach centered on an expressive pre-processing step using SAX followed by the application of hidden Markov models over the processed sequential data. This has the benefit of overcoming the limitations of traditional methods based on feature extraction, namely limitations to deal with expressive behavior (flexible relation of both temporal and amplitude axis through patterns) and with individual response differences related to signal dimensionality and numerosity. Multiple criteria for modeling the signal and for defining the classifier parameters are proposed, with the labeling step relying on the calculus of joint probabilities.

These results were supported by initial observations from a collected sample of signals. An extended experimental study is being undertaken for further validation and to characterize the differences among emotion-driven EDA patterns.

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