Touch dynamics for affective states recognition: your smartphone knows how you feel since you unlock it

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***Abstract*—Touch Dynamics is the behavioral biometric trait that regards how the user interacts with devices equipped with touch displays, the dynamic patterns drawn through the swipe movement can be used to identify the user who is accessing the smartphone. In this paper we investigated whether the same data could be used also to recognize some emotional states. To this aim, an Android App was designed to simulate the unlock patterns and collect data needed to calculate numeric features that have been used not only for identification purposes but also to classify three negative affective states: anxiety, stress and depression. Results obtained so far are encouraging and indicate that Random Forest is capable to reach good classification accuracy both on touch numerical features and on negative emotional states classification also exploiting behavior information such the hand and the finger used in the execution.**

Keywords—touch dynamics, swipe features, affective classification, emotions, machine learning.

I. INTRODUCTION

Security systems use biometric traits to establish the identity of a person based on their characteristic features which can be difficult to be counterfeited and cannot be lost or forgotten. Biometric traits can be *Physiological* in the case a direct measure of a human body part can be performed (e.g. iris, fingerprint, etc.) or *Behavioral* in the case in which an action performed by the user is measured (e.g. handwritten signature, walk, etc.). Behavioral biometrics also involve a cognitive aspect because actions performed are learned over time and can change depending on environmental, psycho-emotional and physical conditions [1]. From this perspective, it has been demonstrated that emotional state influences human movements and actions as, for example, speech [2], facial expression [3], body language [4] and writing [5].

The biometric trait taken into consideration in this work is the *Touch Dynamic* referred as behavioral trait related to how the user interacts with a touch screen of a device (e.g. smartphone, tablet). Exploiting touch dynamics in this context, means investigating on features like the pressure applied on the screen, finger-display touch area, the speed of swipes, the variation of the device sensors (e.g. accelerometer), and so on.

One of the advantages of exploiting this biometric trait is total transparency since the user no needs to use unfamiliar devices or wear sensors, or interact differently from his habits, but the data are recorded and analyzed automatically in a natural way. As a side effect of the identification/verification task, due to the intrinsic capabilities of a behavioral biometric, emotional states of the user can also be revealed. In this work negative emotional states (anxiety, depression and stress) have been considered and collected by a specific questionnaire. Results obtained so far indicate that Random Forest is capable to reach good classification accuracy both on touch numerical features and on negative emotional states also exploiting behavior information such the hand and the finger used.

The work is organized as follows: in Section II related works and literature are presented; Section III introduces the negative affective states. In Section IV the smartphone App is described. The dataset and the numeric features are depicted in Section V while Section VI presents the experimental phase and, finally, Section VII contains conclusions and future work directions.

II. RELATED WORK

An important part of studies when considering user behaviors on devices concerns the password entry and how approaching them. Draffin et al. [6] asked 20 users to type their password on a specifically devoted keyboard observing that these micro-behavior features can identify a non-authorized user within 5 keypresses in 67.7% of the time. In [7] 85 users have to enter two numeric PINs (4 and 8 numbers) holding the phone with the left hand and interacting using the right index finger reaching a verification equal error rate under 3.65%. Further studies focused on more complex tasks: in [8] it was required to insert the phrase '*the quick brown fox jumped over the lazy ghost*.' in addition to the common password reaching a minimum identification EER of 12.5 while Meng et al. [9] provided data about the use of a smartphone since 20 users were provided with a phone with an Android software modified to record all the user touches to authenticate different users with an average error rate of about 7.8%. Syed et al. [10] simulated a common everyday interaction task by asking users to search for something in the smartphone (e.g. a specific image within a list of other images), gathering information about the interaction modes of users with three different devices (a 4.8-inch display phone and two tablets of 7 and 10 inches respectively). The study in [11] proposes a simple game of comparing two images, 30 users performed the task on 3 different smartphones for about 3 minutes. In Putri et al. [12] users performed different tasks, for example answer to questionnaires, as well as carry out general web browsing, map searches on Google Maps and small writing task: a Zenfone device was used and 29 users performed recording sessions with a following classification between device owners and imposters. Finally, the work of Liu et al. [13] adopted patterns for user classification and involved 113 users to complete point pattern composed from 4 to 9 steps: 10 samples were collected at the beginning of the experiment and 10 after 7 weeks when 7 users tried to emulate the patterns of the 113 users 5 times; finally, these last patterns have been used as a test to simulate impostors. To the best of authors' knowledge, there are a few works that aim at recognizing emotions from touch dynamics. Gao et al. [14] built a system to recognize four emotional states (Excited, Relaxed, Frustrated and Bored). It was showed that pressure features discriminate frustration states from the other three states. Stroke length features discriminate mainly boredom from a relaxed state. The classification results were interesting since the proposed approach discriminates between 4 emotional states reaching between 69% and 77% of correct recognition. These results highlight the potential of using touch behavior as a non-obstructive way to measure users' emotional states in contexts where touch-based devices are used. Similarly, Maramis et al. [15] use haptic touch data acquired from Android smartphones to unobtrusive and real-life emotion recognition by exploiting the association between four emotions and haptic touch. The proposed method achieves very promising classification accuracy using a mixture of feature extraction and machine learning based classification techniques.

III. THE DASS-42 QUESTIONNAIRE AND AFFECTIVE STATES

Stress, anxiety and depression are responses to the challenges of everyday life and results useful to detect and prevent them before they impact on individual health and daily actions: if a device detects a negative emotional state, an Intelligent System can warn user with appropriate solutions, for example by lightening its work schedule or organizing the environment and the interface in a more relaxing way with suitable icons, colors, sounds and brightness. The *Stress* is a general adaptation syndrome designed to re-establish a new internal balance following changes in internal balance at the humoral, organic and biological levels; in the physical response it shows tachycardia, muscle contraction and other factors typical of the "fight or flight" response.

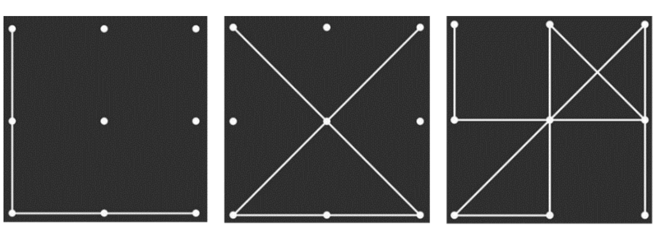

Fig. 1: the three patterns proposed from the task with different difficulty.

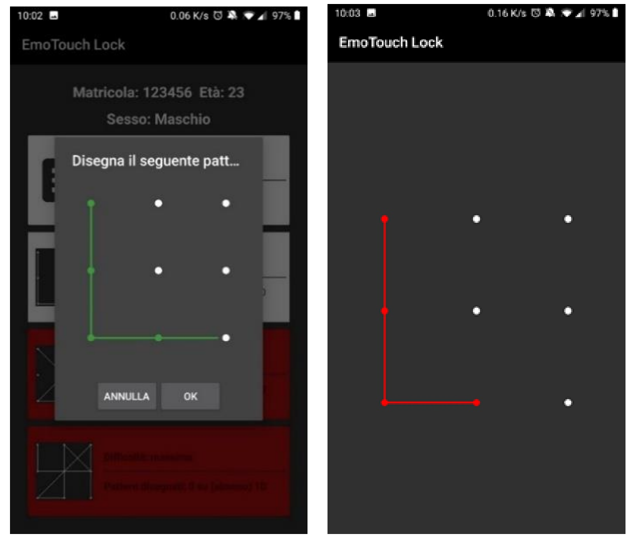

Fig. 2: (left) tutorial tab for the Easy pattern; (right) the execution tab.

The *Anxiety* is a state characterized by intense feeling of concern and fear, often unfounded, related to a specific environmental stimulus associated with a failed response of adaptation and is often accompanied by palpitations, shortness of breath and tremor with response of "fight or flight". *Depression* is a disorder characterized by mood episodes accompanied by low self-esteem and loss of interest in normally pleasant activities. It is a debilitating disease that involves both the affective and cognitive spheres affecting work, sleep and physical health with a strong impact on style and quality life.

The DASS-42 questionnaire is called '*Depression, Anxiety and Stress Scales*' [16] and was created by the University of New South Wales (Australia) to achieve comparable results about the three emotions evaluation. It consists of 42 questions, 14 for each category and refers to the last 7 days of the interview and each answer is evaluated on the basis of 4 points with a final score as the sum of individual ones. The scale has been already used in tasks similar to those considered here and, specifically, it has been used to determine writers' emotional states when performing handwriting which is considered a behavioral biometrics like touch dynamics [5]. In this work, after an entire pattern execution session, the questionnaire is used to assign a label to the collected subject's data, associating them to his affective state while performing its experimental session.

IV. THE EMOTOUCH LOCK APP

To date there is no available public dataset related to touch tasks and emotional states. To the aim of data collection, an application has been specifically developed.

The application is called *EmoTouch Lock* (EMOtion and TOUCHdynamics in a LOCKscreen) since it was designed to simulate unlock patterns on an Android smartphone device collecting data on user touch behaviors.

At the first usage, the user is required to provide age and gender info, successively 4 tabs are displayed: Survey and

Easy/Medium/Difficult Pattern. The first one allows access to the DASS-42 questionnaire while the three 'pattern tabs' offer a touch sequence to be executed (Fig.1) with different difficulty due to the number of swipes to be executed.

When a specific task is proposed by the system, for example the *Easy* one, a pop-up appears (Fig.2, left) containing a tutorial showing how to complete the sequence without leaving the finger from the touch screen. Next, a screen with the 9 points to be linked following the proposed pattern is presented (Fig. 2, right).

User data are recorded from the first touch until the finger is lifted; whether the inserted pattern is correct or not the data are sent to the server.

V. SWIPE AND NUMERICAL FEATURES

The data and the raw values acquired by the sensors must be transformed and adapted to be used effectively in machine learning classifiers and models.

A. Swipe Dynamics

The first stage of is swipe extraction. A *swipe* is a touch interaction with no sensible curvature. Figure 3 provides an example of the execution of the 'Medium' difficulty task.

Considering the pattern execution sequence (from A to D), black dots are the sampled coordinates projections of the user touch while red dots highlight instants where the touch *changes direction*: a swipe is the sequence of dots sampled until a direction change (the ideal red line in the figure). To determine the red points in a pattern execution, the *angular values* calculated with respect to the horizontal axis between a sequence of three black points has been considered and empirically matched against a threshold of 135 degrees.

B. Numerical Features

A set of numerical features have been extracted from the swipe as reported in Table I. In other words, 14 features characterize each single swipe. Among the others, '*line deviation'* and the '*swipe direction'* are the most important. The former represents a change in the touch movement while the latter considers the deviation of the movement from the 'ideal' trajectories requested from the task, indicating how the user designed a swipe in a linear manner.

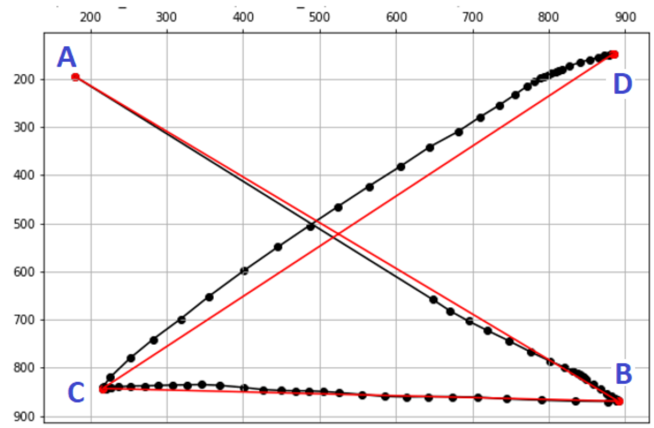

Fig. 3: the plot of touch movements (black dots) while executing the 'Medium' pattern. Red dots highlight direction changes (swipes, red lines).

TABLE I.

ID	Feature	Description
1	distance	Swipe length
2	speed	Swipe speed = length / duration
3	lineDev	Relationship between distance and displacement
4	PressDev	Pressure variance on the screen
5	sizeVar	Screen contact area variance
6	lineDir	Swipe direction
7	PPtouchsPerc	Percentage of touches in a certain direction considering the points
8	PPangleVar	Variance of the direction of the vector of point sequence
9	SPtouchsPerc	Percentage of touches in a certain direction as 'start point - point x'
10	SPangleVar	Variance of the direction of the vector as 'start point - point x'
11	EPtouchsPerc	Percentage of touches in a certain direction as 'end point - point x'
12	EPangleVar	Variance of the direction of the vector as 'end point - point x'
13	YaxisAngleVar	Variance of the angle formed between points and the Y axis
14	XaxisAngleVar	Variance of the angle formed between points and the X axis

Numerical features calculated from the drawn swipes in each task.

Some features (Table I) have been calculated in different ways based on the points contained in a swipe as follows:

- PP: the feature has been calculated point-to-point, i.e. all the points are considered in pairs (point 1-point 2, point 2-point 3, point 3-point 4, etc.)
- SP: the first point of the pair is always the starting point of the sequence (start point - point 1, start point - point 2, start point - point 3, etc.)
- EP: unlike SP, indicates that the end point is taken into account rather than the starting point

VI. Experimental Session

A. Experimental Setup

In order to perform experiments, 40 distinct subjects (university students, mean age of 22 years, 6 females and 34 males) have been asked to execute the swipe tasks, with a minimum of 5 patterns for each difficulty level, for a total of at least 15 patterns per users. The only constraint was that a new pattern could be executed only after (at least) 10 minutes after completion of the previous one while the subjects used the app in an uncontrolled real environment, recording data on the train, walking, sitting and so on; moreover, there was not a limit on the interaction mood since subjects were able to complete the patterns using the most comfortable hand and fingers (however, such information have been requested at the end of each task execution). Due to the freedom given to participants, not all of them reached the same number of recorded patterns and so, after a data cleaning operation, to maximize the possibility of comparisons it was decided to divide them into three experimental groups, also overlapped to consider the subject skills progression over time. So that, the entire dataset has been balanced into the following:

- Dataset A: 40 users with 6 attempts for each task
- Dataset B: 22 users with 10 attempts for each task
- Dataset C: 10 users with 16 attempts for each task

B. Machine Learning Classification

At the initial stage, a set of classifiers has been adopted to evaluate classification accuracy at single swipe level (i.e. not at entire pattern level). The following have been considered:

- J48: algorithm for the generation of a C4.5 decision tree, pruned and not pruned
- Support Vector Machine: a model that assigns one of two classes separated through support examples
- Random Forest: an overall classifier of decision trees
- Bayesian Network: a probabilistic model that exploits variables and their conditional dependencies
- Naive Bayes: requires knowledge of the a priori and conditional probabilities related to the problem.

TABLE II.

Classifier	Accuracy
J48	65 %
SVM	43 %
Random Forest	**76 %**
Bayes Network	56 %
Naïve Bayes	47 %

Classification results of swipes with features on the whole dataset.

TABLE III.

	Stress	Anxiety	Depression
basic features (Table 1)	**73.6 %**	69.5 %	72.2 %
basic features (Table 1) + hand and finger data	**78 %**	74.1 %	**77.2 %**

Classification results on the affective state recognition exploiting further behavioral features with Random Forest classifier.

Classification results, considering the whole dataset about the swipe features goodness, are in Table II while a *10-fold cross validation* mode has been employed to reduce the impact of the variance while choosing the training and test examples. The best performance has been obtained with the Random Forest: 76% of accuracy.

Random Forest has been used for further tests and results related to negative emotional states classification with 10-fold cross validation are reported in Table III where 15 users has been randomly selected with 184 swipe samples each. it can be observed that the recognition accuracy is near 70% and all results improve when exploiting the further behavioral feature set. The best recognized emotional state is the Stress with 73.6% and 78% respectively while the Depression is the one that takes the most advantage from new features (+5%).

Finally, the Random Forest classifier has been employed to perform the *identity verification* tests, checking if it is possible to associate each single swipe to the user who produced it in order to highlight its characterization through this behavioral biometric trait. In other words, understand if it is possible to have identity verification as well as emotional state recognition at unlock time. In this case due to the reduced dimension, for each of the three sub-dataset a *leave-one-out* setup has been adopted: in this way, if the dataset contains *n* swipe feature vectors, there are used *n-1* for the training and the remaining one for the test for *n* times. As evaluation metric the *Equal Error Rate* (EER) has been chosen: it indicates how the proportion of false acceptances is equal to the proportion of false rejections (the lower the EER value, the higher the accuracy of the biometric system is).

TABLE IV.

Dataset	EER
A	23%
B	16%
C	**12%**

User identity classification exploiting swipe numerical features.

From Table IV emerges that best-recognized subjects are those having the more number of attempts for each task execution (dataset C): although they are smaller in number than the other groups, can be considered their greater characterization due to increasingly specific data, along with a progression in the mastery of the execution skills. Results are noteworthy, with the highest error of only 23% on dataset A and the best classification results on dataset C where error decreases about 50%.

VII. Conclusion and Future Work

This study introduces the Touch Dynamics method as biometric trait able to recognize a users' emotional states as information useful to characterize and distinguish users as well as to adapt contents and behavior of smartphones. A set of tasks related to touch un-lock patterns have been exploited to extract numerical features on a smartphone devices demonstrating that that touch swipes are useful for recognizing the identity with an EER of 12% for users with a huge practice using the Random Forest.
The exploit of emotional states has been performed adopting the DASS-42 questionnaire whose results will be further inquired in future studies; in this case, classification accuracy is around 70%. Starting from this work several improvements are possible, such as adding more features, classification methods and swipe patterns to test how users improve their performances. Equally necessary is to have the users balanced between male and females along with a feature selection study to inquire which are the features with the major informative contribution. Furthermore, the proposed methodology could be adapted to new contexts, exploiting swipes made by users while moving around the device interface or in other applications.

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