Handwriting and Drawing Features for Detecting Negative Moods

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Abstract. In order to provide support to the implementation of on-line and remote systems for the early detection of interactional disorders, this paper reports on the exploitation of handwriting and drawing features for detecting negative moods. The features are collected from depressed, stressed, and anxious subjects, assessed with DASS-42, and matched by age and gender with handwriting and drawing features of typically ones. Mixed ANOVA analyses, based on a binary categorization of the groups, reveal significant differences among features collected from subjects with negative moods with respect to the control group depending on the involved exercises and feature's categories (in time or frequency of the considered events). In addition, the paper reports the description of a large database of handwriting and drawing features collected from 240 subjects.

1 Introduction

Early detection of diseases is the key for health care. The earlier a disease is diagnosed, the more likely it is that it can be cured or successfully managed. When you treat a disease early, you may be able to prevent or delay problems from the disease.

Several chronic diseases are asymptomatic and can be diagnosed by special checkups. Unfortunately, such checkups are costly and often invasive and therefore they are not chosen on the basis of possible trade-offs in terms of costs and benefits. On the other hand, the detection of illnesses can be also based on the analysis of simple non invasive human activities (speeches, body motions, physiological data, handwritings, and drawings) [3, 12]. In particular, it has been shown that several diseases like Parkinson and Alzheimer have a sensible effect on writing skills [16].

Handwriting is a creative process which involves conscious and unconscious brain functionalities [15]. Indeed, handwriting and drawing analyses on paper has been successfully used for cognitive impairment detection and personality trait assessment [12, 14, 18, 25]. To this aim, several tests like the clock drawing test (CDT) [10], the mini mental state examination (MMSE) [9] and the house-tree-person (HTP) [11] have been designed in the medical domain. Recently, thanks to the development of novel technological tools (scanners, touch displays, display pens and graphic tablets), it is possible to perform handwriting analyses on computerized platforms. Such computerized analyses provide two main advantages: i) the collection of data includes several non-visible features such as pressure, pen inclination, in air motions; ii) data includes timing information which enable the *online*analysis the whole drawing and/or handwriting process instead of analyzing a single *offline* snapshot representing the final drawing. Accordingly tests for detecting brain stroke risk factors and neuromuscular disorders, or dementia, have been computerized [10, 17, 19].

Accurate recognition of emotions is an important social skill that enable to properly establish successful interactional exchanges [6, 5, 8, 22]. Indeed, emotions and moods affect cognitive processes, such as executive functions, and memory [20, 26] and have an effect on handwriting, since it involves visual, sensory, cognitive, and motor mechanisms.

The first study that applied handwriting analysis for the detection of emotions is [12]. It presents a public database (EMOTHAW) which relates emotional states to handwriting and drawing. EMOTHAW includes samples of 129 participants whose emotional states, namely anxiety, depression, and stress, are assessed by the Depression-Anxiety-Stress Scales (DASS-42) questionnaire [13]. Handwriting and drawing tasks have been recorded through a digitizing tablet. Records consist in pen positions, pen states (on-paper and in-air), time stamps, pen pressure and inclination. The paper reports also a preliminary analysis on the presented database, where several handwriting features, such as the time spent “in air” and “on paper”, as well as, the number of strokes, have been identified and validated in order to detect anxiety, depression, and stress.

This paper extends the work in [12] presenting an enlarged database of 240 subjecta and proposing also some novel data-analysis features in order to measure the effects of negative moods on handwriting and drawing performances. Mixed ANOVA analyses, based on a binary categorization of the groups (i.e., typical, stressed, anxious, and depressed subjects), reveal significant differences among features collected from subjects with negative moods with respect to the control group depending on the involved exercises and feature’s categories (in time or frequency of the considered events).

2 Handwriting analysis for the detection of negative moods

2.1 Handwriting Analysis

Handwriting analysis have been carried out using an INTUOS WACOM series 4 digitizing tablet and a special writing device named Intuos Inkpen. Participants were required to write on a sheet of paper (DIN A4 normal paper) laid on the tablet. Fig. 1 shows the sample acquired from one participant. While the digital signal is visualized on the screen, it is also visible on the paper (due to the inkpen), and the participant normally looks at the paper. There is a human supervisor sitting next to the participant, controlling a specifically designed acquisition software linked to the tablet.

For each task, the software starts automatically to capture data as soon as the inkpen touches the paper. The recording is stopped manually by the supervisor but this does not affect the collected timing information since the software does not record any data while the pen is far from the tablet. The software stores the data in a svc file (a simple ASCII file that can be opened with any text editor).

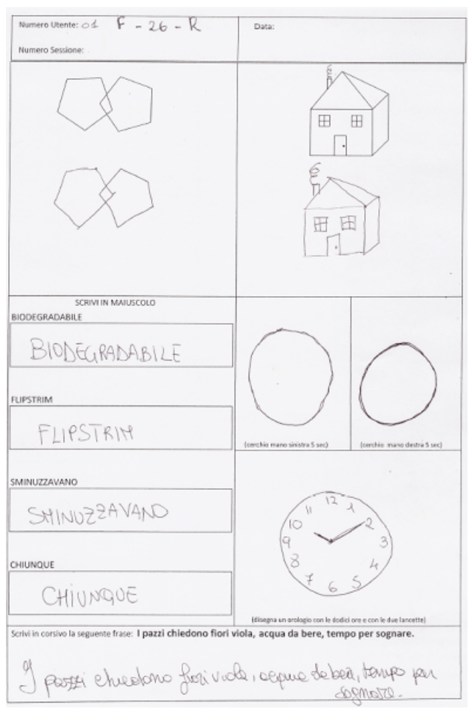

Fig. 1. A4 sheet with the set of tasks filled by one participant.

During each experimental task, the following information is continuously captured with a frequency of 125 Hz (see also figure 2):

1. position in x-axis;
2. position in y-axis;
3. time stamp;
4. pen status (up = 0 or down = 1);
5. azimuth angle of the pen with respect to the tablet;
6. altitude angle of the pen with respect to the tablet;

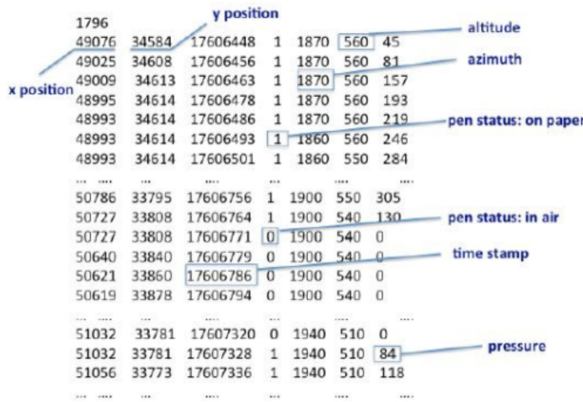

Fig. 2. Extract of an svc file.

7. pressure applied by the pen on the paper.

Using this set of dynamic data, further information such as acceleration, velocity, instantaneous trajectory angle, instantaneous displacement, time features, and ductus-based features (see Section 4.2) can be inferred. The system has the nice property to capture in-air movements (when the inkpen is very close to the paper) which are lost using the on-paper ink. The in-air information has proven to be as important as the on-surface information [12, 23, 21]. In particular, in [12] several simple features exploited this in air (up) or on paper (down) information. In this paper we performed a more detailed classification by partitioning the pen states into three categories:

– **up**, recorded with state 0;
– **down**, recorded with state 1;
– **idle**, not recorded but recognizable using time stamps. Usually the tablet collects information with a frequency of 125 Hz (one row each 0.008 sec). When two consecutive row are separated by more than 0.008 sec the missing time is considered as an idle state.

The tasks acquired by the tablet are the following (see Fig. 1):

1. copy of a two-pentagon drawing;
2. copy of a house drawing;
3. writing of four Italian words in capital letters (BIODEGRADABILE (biodegradable), FLIPSTRIM (flipstrim), SMINUZZAVANO (to crumble), CHIUNQUE (anyone));
4. loops with left hand;
5. loops with right hand;
6. clock drawing;
7. writing of the following phonetically complete Italian sentence in cursive letters (I pazzi chiedono fiori viola, acqua da bere, tempo per sognare : Crazy people are seeking for purple flowers, drinking water and dreaming time).

2.2 Negative moods: Depression, Anxiety and Stress Scales

In order to measure the subject current mood, the Italian version [24] of *DASS-42* (Depression, Anxiety and Stress Scales) [13] was administered to each participant. This is a self-report questionnaire composed by 42 statements measuring depressive, anxious, and stress symptoms. Each scale (D – Depression; A – Anxiety; S – Stress) is made up by 14 statements. The scale is based on the assumption that depressed, anxyous, and stressed mood are not categorical (that is disorders), but dimensional constructs [13]. Hence, the mood can change from normal to severe state along a continuum. Psychometric properties of this scale were originally assessed in [13] on a large non-clinical sample (2.914), composed mostly by university students, identifying mood (depressed, anxious, stressed) severity ratings from normal to extremely severe, as showed by Table 1. Later, several studies assessed DASS psychometric properties (competing models of the structure, reliabilities, convergent and discriminant validity) [1, 2, 4, 7]. The DASS administration procedure requires that for each statement in the questionnaire, the subject is asked "how much it applies to him/her over the past week". Participant answers are rated on a 4 points Likert scale (0 = never, 1 = sometimes; 2 = often; 3 = almost always).

	Depression (D)	**Anxiety (A)**	**Stress (S)**
Normal	0 − 9	0 − 7	0 − 14
Mild	10 − 13	8 − 9	15 − 18
Moderate	14 − 20	10 − 14	19 − 25
Severe	21 − 27	15 − 19	26 − 33
Extremely Severe	28+	20+	34+

Table 1. DASS-42: Severity rating [13].

3 The Database

For the data collection, 240 subjects (126m, 114f) between 18 and 32 years ($M = 24.58; SD = \pm 2.47$) were recruited at the Department of Psychology of the Università degli Studi della Campania "L. Vanvitelli" (Caserta, Italy). All subjects were Master or BS students and volunteered their participation to the study. Participants were individually tested in a laboratory free of auditory and/or visual disturbances. At the beginning of the experiment, the study has been explained to the participant and, subsequently, he signed an informed consent. Before administering the DASS through a computer aided procedure and collecting handwriting samples, participants were informed that they can withdraw their data at any point of the data collection process. In addition, once collected, data were automatically anonymized in a way that experimenters would not be able later to identify participant's identities. Each participant first completed the *DASS-42* questionnaire and then the handwriting tasks. Table 2 shows the percentage of co-occurrence of emotional states resulting by DASS scores.

	depressed		**not depressed**	
	stressed	**not stressed**	**stressed**	**not stressed**
anxious	17.1	4.2	10.8	10.4
not anxious	4.2	3.3	5.4	44.6

Table 2. Percentage of co-occurrence of emotional states resulting by DASS scores.

Aggregating the data it can be observed that 44.6% of subjects report a normal mood; 19.1% a single negative mood (3.3% depression, 10.4% anxiety, 5.4% stress); 19.2% two negative moods (4.2% depression and anxiety; 4.2% depression and stress; 10.8% stress and anxiety); 17.1% all three negative moods (depression, anxiety and stress). Scoring details can be found at the following link https://sites.google.com/site/becogsys/emothaw.

4 Database evaluation

4.1 Evaluation Setup

A set of students were selected from the database described in section 3 and divided in three dichotomous classes according to the DASS-42 scores:

D (Depression) Scale: depressed/not depressed group (DG/N-DG);
A (Anxiety) Scale: anxious/not anxious group (AG/N-AG);
S (Stress) Scale: stressed/not stressed group (SG/N-SG).

The three groups had the following characteristics:

D Scale: 42 subjects (23m and 19f) with depressed mood (DG) aged from 19 to 30 years ($M = 24.4; SD = 2.6$) and 42 subjects (23m and 19f) with non-depressed mood (N-DG) aged from 19 to 32 years ($M = 25.10; SD = 2.4$);
A Scale: 71 subjects (33m and 38f) with anxious mood (AG) aged from 19 to 30 years ($M = 24.30; SD = 2.4$) and 71 subjects (33m and 38f) with non-anxious mood (N-AG) aged from 18 to 32 years ($M = 24.69; SD = 2.5$);
S Scale: 50 subjects (27m and 23f) with stressed mood (SG) aged from 19 to 31 years ($M = 23.88; SD = 2.4$) and 50 subjects (27m and 23f) with non-stressed mood (N-SG) aged from 20 to 29 years ($M = 24.76; SD = 2.05$).

Subjects with negative mood (DG, AG and SG) had moderate, severe and extremely severe scores, while typical subjects (N-DG, N-AG, N-SG) had normal scores into the three (depression, anxious, stress) DASS scales (see Table 1).

In order to assess whether writing and drawing features (extracted from tasks 1, 2, 3, 6 and 7, described in section 2.1), of subjects with negative (depressed, anxious and stressed) mood significantly differ from typical ones, two Mixed ANOVAs were performed. The first concerns timing-based and the second ductus-based features. Timing-based futures measures the time spent by the subject for each specific task on each pen state (Down, Up, Idle). Ductus-based features measure the number of times the subject has changed the pen state, while performing a task.

With respect to timing features, three $2 \times 3 \times 5$ mixed ANOVAs (one for each Scale: depression, anxiety, stress) were performed, with Group (depressed/not depressed (DG/N-DG); anxious/not anxious (AG/N-AG); stressed/not stressed (SG/N-SG)) as between factor, and features (tUp, tDown, tIdle) and tasks (I [pentagon drawing], II [house drawing], III [words in capital letter], VI [clock drawing], VII [writing of sentence]) as within factors.

With respect to the ductus features, three $2 \times 3 \times 5$ mixed ANOVAs (one for each Scale: depression, anxiety, stress) were performed, with Group (depressed/not depressed (DG/N-DG); anxious/not anxious (AG/N-AG); stressed/not stressed (SG/N-SG)) as between factor, and features (nUp, nDown, nIdle) and tasks (I [pentagon drawing], II [house drawing], III [words in capital letter], VI [clock drawing], VII [writing of sentence]) as within factors.

4.2 Results

Table3 shows that 74% of depressed subjects is also anxious and stressed, 45% of anxious subjects is also depressed and stressed, and 80% of stressed subjects is also depressed and anxious, suggesting co-occurrences of the three negative moods. These co-occurrences seem contradict the aims of the DASS scale, whose "task was to develop an anxiety scale that would provide maximum discrimination from the BDI and other measures of depression" (Lovibond & Lovibond 1995[13], p. 336). Further investigations are in order to assess whether these co-occurrences are indicating a real co-occurrence of the negative moods or overlapping factors among the three DASS scales defined into the DASS questionnaire.

Timing-based features. Table 4 reports on the rows the three DASS scales (depression, anxiety and stress), each partitioned in the associate negative (DG, AG, and SG) and normal (N-DG, N-AG, N-SG) mood respectively, and in turn each partitioned into the three pen-state timing features (tUp, tDown, tIdle). Columns report for these features the mean (M) and standard deviation (SD) for each of the 5 performed exercises. Data in bold indicates features where statistically significant differences are observed.

D Scale. A mixed ANOVA shows there are significant differences for Group [$F(1,82)=4.26$; $p=.042$; M(DG)=10.43 sec; M(N-DG)=9.22; SD=0.41; MD=1.21 sec]. The Group $\times$ Features $\times$ Exercise interaction shows significant differences:

- in the exercise I for features:

DG	**anxious**	**not anxious**
stressed	73.8	4.8
not stressed	9.5	11.9

AG	**depressed**	**not depressed**
stressed	45.1	28.2
not stressed	5.6	21.1

SG	**depressed**	**not depressed**
anxious	80.0	4.0
not anxious	8.0	8.0

Table 3. Percentage of co-occurrence of emotional state in DG, AG, SG Group.

DASS-42 Scales	groups	features	ex. I		ex. II		ex. III		ex.VI		ex. VII	
			M	*sd*	*M*	*sd*	*M*	*sd*	*M*	*sd*	*M*	*sd*
Depression Scale	*DG*	*1 (tUp)*	8.39	1.12	14.66	1.13	14.09	0.70	13.86	1.05	9.83	0.70
	N-DG		6.16		12.95		12.65		13.30		9.31	
	DS	*2 (tDown)*	**11.62**	0.79	19.06	1.18	**16.22**	0.49	13.50	0.71	16.12	0.43
	N-DG		**9.00**		16.87		**14.72**		11.80		14.95	
	DG	*3 (tIdle)*	**2.61**	0.41	4.55	0.48	3.44	0.32	5.41	0.80	3.17	0.33
	N-DG		**1.42**		3.37		3.03		5.90		2.93	
Anxiety Scale	AG	*1 (tUp)*	**8.47**	0.65	14.65	0.77	**14.09**	0.49	15.38	1.01	8.89	0.52
	N-AG		**6.25**		12.91		**12.70**		13.56		9.54	
	AG	*2 (tDown)*	**11.58**	0.53	**19.27**	0.80	**16.25**	0.37	14.80	0.68	15.77	0.34
	N-AG		**9.03**		**15.57**		**14.58**		11.63		15.09	
	AG	*3 (tIdle)*	**2.56**	0.30	**5.04**	0.43	3.84	0.39	7.87	1.24	3.02	0.82
	N-AG		**1.46**		**3.10**		3.57		5.95		4.33	
Stress Scale	SG	*1 (tUp)*	6.94	0.70	13.46	0.76	13.45	0.58	13.84	0.78	9.14	0.77
	N-SG		5.72		12.71		12.33		13.12		9.60	
	SG	*2 (tDown)*	10.31	0.55	17.89	0.90	15.21	0.38	13.07	0.58	15.31	0.41
	N-SG		9.06		15.28		14.52		11.47		15.18	
	SG	*3 (tIdle)*	2.16	0.31	**4.57**	0.39	3.73	0.38	5.78	0.64	3.38	1.16
	N-SG		1.28		**2.67**		3.51		5.23		4.96	

Table 4. Mean (M) and Standard Deviation (SD) of timing-based on features of each exercise. Data in bold indicates features that significantly differ ($p < .05$) in the binary categorization of each DASS scale, i.e., depressed/not depressed, anxious/not anxious, stressed/not stressed.

  - 2 (tDown) [F(1,82)=5.51; p=.021; M(DG)=11.61 sec; M(N-DG)=8.99 sec; SD=0.78; MD=2.62];
  - 3 (tIdle) [F(1,82)=4.17; p=.044; M(DG)=2.61 sec; M(N-DG)=1.42 sec; SD=0.41; MD=1.18];
- in the exercise III for features:
  - 2 (tDown) [F(1,82)=4.78; p=.032; M(DG)=16.22 sec; M(N-DG)=14.71 sec; SD=.47; MD=1.50].

A Scale. A mixed ANOVA shows significant differences for Group [F(1,140)=11.31; p=.001; M(AG)=10.75 sec; M(N-AG)=9.28; SD=0.31; MD=1.48 sec]. The Group × Features × Exercise interaction shows significant differences:

- in the exercise I for features:
  - 1 (tUp) [F(1,140)=5.77; p=.018; M(AG)=8.46 sec; M(N-AG)=6.25 sec; SD=0.65; MD=2.21];
  - 2 (tDown) [F(1,140)=11.44; p=.001; M(AG)=11.58 sec; M(N-AG)=9.02 sec; SD=0.53; MD=2.55];
  - 3 (tIdle) [F(1,140)=6.50; p=.012; M(AG)=2.55 sec; M(N-AG)=1.45 sec; SD=0.43; MD=1.09];
- in the exercise II for features:
  - 2 (tDown) [F(1,140)=10.80; p=.001; M(AG)=19.27 sec; M(N-AG)=15.56 sec; SD=0.79; MD=3.70];
  - 3 (tIdle) [F(1,140)=10.15; p=.002; M(AG)=5.04 sec; M(N-AG)=3.09 sec; SD=0.43; MD=1.94];
- in the exercise III for features:
  - 1 (tUp) [F(1,140)=4.03; p=.046; M(AG)=14.08 sec; M(N-AG)=12.69 sec; SD=0.49; MD=1.39];
  - 2 (tDown) [F(1,140)=10.41; p=.002; M(AG)=16.25 sec; M(N-AG)=14.55 sec; SD=0.36; MD=1.67];
- in the exercise VI for features:
  - 2 (tDown) [F(1,140)=10.82; p=.001; M(AG)=14.80 sec; M(N-AG)=11.63 sec; SD=0.68; MD=3.17].

S Scale. A Mixed ANOVA shows no significant differences for Group [F(1,98)=3.55; p=.06; M(SG)=9.88 sec; M(N-SG)=9.10; SD=0.29; MD=0.78 sec]. The Group × Features × Exercise interaction shows significant differences:

- In the exercise II for features:
  - 2 (tDown) [F(1,98)=4.28; p=.041; M(AG)=17.89 sec; M(N-AG)=15.26 sec; SD=0.90; MD=2.63]
  - 3 (tIdle) [F(1,98)=11.44; p=.001; M(SG)=4.57 sec; M(N-SG)=2.68 sec; SD=0.39; MD=1.89];

Ductus-based features Table 5 reports on the rows the three DASS scales (depression, anxiety and stress), each partitioned in the associate negative (DG, AG, and SG) and normal (N-DG, N-AG, N-SG) mood respectively, and in turn each partitioned into the three pen-state ductus features (nUp, nDown, nIdle). Columns report for these features the mean (M) and standard deviation (SD) for each of the 5 performed exercises. Data in bold indicates Features where statistically significant differences are observed.

D Scale. A mixed ANOVA shows significant differences for Group [F(1,82)=4.71; p=.033; M(DG)=28.09; M(N-DG)=25.40; SD=0.87; MD=2.70]. No significant differences are observed for Group × Feature × Exercise and Group × Exercise

DASS-42 Scales	groups	features	ex. I		ex. II		ex. III		ex.VI		ex. VII	
			M	*sd*	*M*	*sd*	*M*	*sd*	*M*	*1.05*	*M*	*sd*
Depression Scale	*DS*	*1 (tUp)*	12.93	2.03	27.05	1.84	62.31	1.23	25.74	1.05	45.29	1.80
	N-DS		7.40		23.69		61.07		24.62		42.02	
	DS	*2 (tDown)*	**13.29**	**2.00**	**27.05**	**1.78**	**62.69**	**1.39**	**26.40**	**1.05**	**45.93**	**1.82**
	N-DS		**7.90**		**24.26**		**60.05**		**25.12**		**41.50**	
	DS	*3 (tIdle)*	10.64	1.60	21.40	2.22	25.74	1.14	19.86	2.11	10.05	0.93
	N-DS		8.12		16.90		9.17		18.02		11.14	
Anxiety Scale	*AS*	*1 (tUp)*	**12.17**	1.28	26.14	1.06	60.75	0.70	27.97	1.51	41.69	1.17
	N-AS		**7.69**		23.44		60.39		24.85		42.37	
	AS	*2 (tDown)*	12.59	1.27	26.38	1.06	60.90	0.82	28.54	1.49	41.66	1.18
	N-AS		8.21		23.96		58.87		25.35		41.59	
	AS	*3 (tIdle)*	11.23	1.11	**20.73**	1.42	10.44	0.82	22.46	2.12	10.27	0.80
	N-AS		8.48		**15.90**		10.06		17.87		11.51	
Stress Scale	SG	*1 (tUp)*	10.62	1.64	24.80	1.25	61.28	0.99	25.70	1.02	42.96	1.62
	N-SG		7.12		22.76		59.86		25.24		42.22	
	SG	*2 (tDown)*	11.18	1.62	25.00	1.25	61.72	1.08	26.30	1.02	42.96	1.61
	N-SG		7.64		23.26		58.82		25.72		41.94	
	SG	*3 (tIdle)*	8.80	1.14	**21.28**	1.29	10.54	1.00	19.12	1.65	10.40	0.90
	N-SG		7.14		**15.12**		9.70		16.62		11.20	

Table 5. Mean (M) and Standard Deviation (SD) of ductus-based on features of each exercise. Data in bold indicates features that significantly differ ($p < .05$) in the binary categorization of each DASS scale, i.e., depressed/not depressed, anxious/not anxious, stressed/not stressed.

interactions. Conversely, Group × Feature interaction shows significant differences between DS and N-DS for the feature 2 (nDown) [F(1,82)=4.89; p=.030; M(DG)=35.07; M(N-DG)=31.76; SD=1.05; MD=3.03].

A Scale. A mixed ANOVA shows significant differences for Group [$F(1, 140) = 6.16; p = .014; M(AG) = 27.59; M(N - AG) = 25.34; SD = 0.63; MD = 2.22$]. The Group × Features × Exercise interaction shows significant differences:

- In the exercise I for features:
  - 1 (nUp) [F(1,140)=6.06; p=.015; M(AG)=12.16 sec; M(N-AG)=7.69 sec; SD=1.28; MD=4.48];
- In the exercise II for features:
  - 3 (nIdle) [F(1,140)=5.75; p=.018; M(AG)=20.73sec; M(N-AG)=15.90 sec; SD=1.42; MD=4.83].

S Scale. A mixed ANOVA shows significant differences for Group [F1,98=4.16; p=.044; M(SG)=26.88; M(N-SG)=24.95; SD=0.66; MD=1.92]. The Group × Features × Exercise interaction shows significant differences:

- In the exercise II for features:
  - 3 (nIdle) [F(1,98)=7.51; p=.007; M(SG)=21.28 sec; M(N-SG)=15.12 sec; SD=1.42; MD=6.16].

5 Conclusion

This paper present an enlarged and refined handwriting database for detecting negative moods (depression, anxiety and stress), and introduces the extraction of a novel time-based handwriting feature indicating the idle subject state. Mixed ANOVA analyses, based on a binary categorization of the groups, reveal significant differences among features collected from subjects with negative moods with respect to the control group depending on the involved exercises and feature categories (in time or frequency of the considered events). In addition, our preliminary investigation shows that the type of negative mood (depressed, anxious or stressed) affects the drawing and handwriting tasks in a different way, considering that some exercises and features are important to detect one specific negative mood but not the others. As a future development, a plan to exploit similar features in order to detect personality traits is featured. Can some personality traits be extracted from handwriting?

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