A Study of Colour Using Mindwave EEG Sensor

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Abstract. Human-Computer Interaction (HCI) is a multidisciplinary research area aiming the design of user-friendly systems. Even though systems are increasingly complex, recurring more and more to multimodal interactions, there are very basic aspects, such as colour and its correct perception, that continue to be crucial for effective and pleasurable communication. These aspects will be reflected in several areas and may be particularly useful in teaching-learning systems.

Thus, we made an experiment designing a study allowing the identification of shapes, determined by the correct perception of certain colour combinations. Hence, we implemented a colour test similar to the Ishihara Colour Blindness Test, but instead of showing numbers it shows objects and several different shapes. In this experiment, we evaluated the users' responses and their feedback regarding the ease of determining the shapes in question, resulting from certain colour combinations. Additionally, we used an EEG signal to determine neurophysiological aspects that are impossible to manipulate with in relation to each displayed figure. From this, it was possible to determine aspects such as the levels of immersion, fatigue and stress caused by each combination.

Keywords: EEG · Mindwave · Fatigue · Immersion · Stress · Visual perception

1 Introduction

1.1 Contextualization

HCI is a growing and increasingly important area. This area is no longer just about designing user-friendly systems, but more and more attention is being given to the inclusion of innovative new forms of interaction and multimodal interactions. Although these increasingly innovative aspects, there are pertinent and fundamental features on which we consider crucial their true understanding. In this sense, we consider that the presentation of colours and their combination may affect considerably the users' perceptions.

Thus, we designed a study allowing the identification of shapes, determined by the correct perception of certain colour combinations, particularly important in multimodal interfaces where these basic aspects should represent the lowest possible cognitive load.

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Hence, we implemented a colour test similar to the Ishihara Colour Blindness Test [1], but instead of showing numbers it shows objects and several different shapes. There are 15 different levels, and in each level the participant should select one of the three answer options corresponding to the form that he/she sees. The test has a limit of 5 min. Although these types of tests are primarily used for the diagnosis of colour blindness, we believe that their use in non-colour-blind people may provide valuable insight into the recommendations to follow regarding certain colour combinations to be used at interfaces.

Colour is one of the most curious aspects of visual perception, so different colour perception could be found also in differences in brain activity. Colour combinations also influence legibility [2] and the inappropriate use of colours can result in higher levels of visual discomfort and poor reading performance [3]. Huang [4] found that visual search performance can be significantly affected by colour combinations. Therefore, we decided to use the electroencephalogram (EEG) signal to detect several parameters levels for the recognition of visual forms in an environment that is difficult to perceive. For that, we used Neurosky Mindwave headset, a portable device that was generally utilized to detect and measure electrical activity of the user's forehead. After the acquisition, the signal was studied in time and in frequency for extraction of parameters of interest. In this experiment, the idea is to confirm which combinations generate less fatigue, stress and immersion to provide faster and easier interactions freeing the user to more complex tasks. To compute fatigue, stress and immersion parameters the energy of important waves like Theta, Beta and Alpha was considered.

1.2 HCI and BCI

HCI is an expanding research area with lot of development in recent years. Most of the work in this area has as the concern the design of user-friendly systems and the most recent ones have as a concern the use of innovative interfaces such as voice, vision, gestures, virtual reality or augmented reality systems [5, 6]. Direct Brain-Computer Interface (BCI) adds a new set of possibilities to HCI [7].

BCI is a way of interaction between individuals and computers don't using any muscle, controlled through individuals' brain activity captured with specific equipment. For Wolpaw et al. [8], BCI is a communication system having two adaptive components complementing each other reciprocally. This author adds that a BCI is a communication system that allows an individual to convey her/his intention to the external world by purely thinking without depending on the brain's normal output channels of nerves and muscles [9].

Brain computer interfaces have been applied in several fields of research from medical [10–13], smart environments [14], neuromarketing and advertisement [15], educational [16, 17] and self-regulation, games and entertainment [18], and Security and authentication fields [19]. The recording of cortical neuronal activity can be done in different ways in BCI systems for instance through EEG (Electro-Encephalo-Graphy), where several electrodes are placed on the scalp. More and more researches use EEG to determine the cognitive load of visual information [20, 21].

Even though EEG has been used for diversified areas the present study used it to determine the visual perception of a certain form according to certain colour combinations. Although we used isolated figures the idea will be to extend these concepts for more complex applications and environments. The users are increasingly demanding and if the products they use are not intuitive and clear they easily abandon them. One of the basic aspects of any interaction lies in the good visual perception of the information, being the colours and their correct combination in their genesis. The colours affect the users' perception which may have an impact on the cognitive performance of tasks. Therefore, it is of great importance the obtaining, processing and feedback of visual information using EEG as a way to reinforce the recommendations for digital interface optimization design.

Hence, in this paper, we used BCI from the viewpoint of one aspect of multimedia interactions, the colour. We consider the colour mainly important for a good visual perception, however some authors also established the motivational factors related to colour and layout [22].

2 Methodology and Procedure

2.1 Main Goals

The main objective of this work was to investigate the effect of colour on brain dynamics in the analysis of complex figures, including different colours combinations to obtain forms. Thus, we are interested in understanding what happens in terms of the energy of the Theta, Beta and Alpha waves in each of the analysed figures, and consequently analyse the levels of Fatigue, Immersion and Stress in each one having an indication of the ease with which colour is perceived. Therefore, our study intended to address the following questions: Q1 - What are the levels and combinations that allow faster response times?; Q2 - Which levels and colour combinations have the highest levels of Fatigue, Immersion and Stress?

2.2 Experimental Design

The experiment was made in a usability laboratory, a calm and controlled environment in order to avoid interruptions. It consisted of a sequential visualization of fifteen squares having each one a form written in a certain combination of foreground and background colours not completely linear but consisting of dots of different sizes, colours and proximity distances.

There are 15 different figures, and in each one the person has to select one of the three answer options depending on what he/she sees (Fig. 1). Associated with each level, there will be a question to which the participants have to answer: "What is the shape you can see?". During this task, each figure was presented at the center of the screen along with the answer options. There is no time limit, for participants to respond. The answer consists of selecting the correct option, followed by the confirmation of that answer by a second click. After this, there is a pause with a white screen for 1 s and a new image appears (Fig. 2).

It should be noted that the location on the screen as well as the size of the images did not change. The participants were also asked not to blink and not to move their eyes, and the body during the visualization of the screens. The purpose of this procedure was

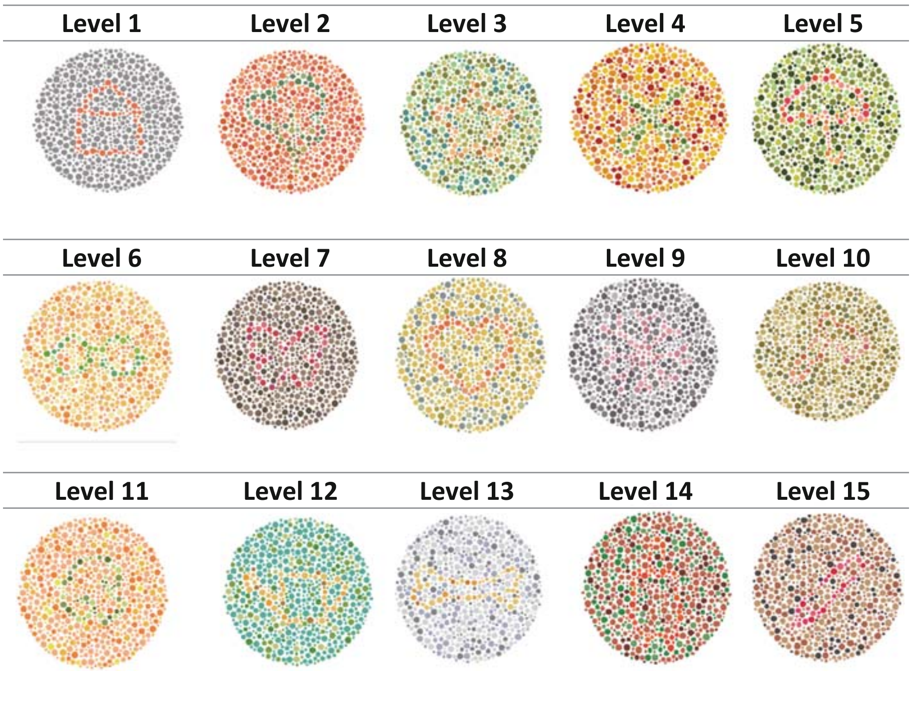

Fig. 1. Levels of the game

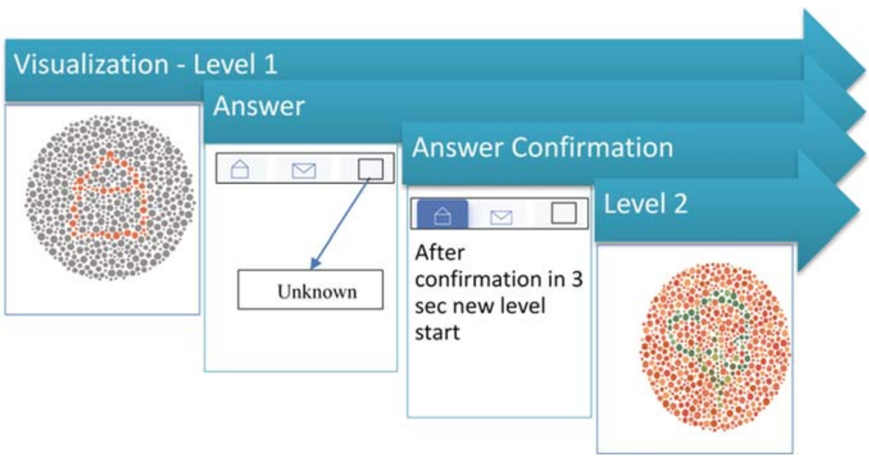

Fig. 2. Experimental design

to eliminate ocular and muscular artifacts, thus avoiding signal loss. At the end of the experiment, users were asked to classify in three groups of difficulty (Low, Medium, High), each one of the figures, according to the ease with which they discover the shapes.

2.3 Data Sample

Twenty-eight participants (8 males and 20 females), aged 18–22 yr (mean: 19 $\pm$ 0.8 yr), were recruited to perform the already mentioned task. All participants provided informed consent prior to participating in the study. At the beginning of the experiment, a questionnaire was made to each participant in order to obtain a more detailed characterization of that population: age, sex, level of education and the existence of visual problems. The purpose of the study was also explained to the participants.

2.4 Feature Acquisition

The feature acquisition was made using the Neurosky's Mindwave device for measuring the brain activity [23]. This simple and affordable device includes two electrodes, one for EEG dataset records (Fp1 channel), another for reference signals (the ear clip) and a power switch. The sample frequency is 512 Hz. The Mindwave EEG sensor processes the brainwave into digital signals and uses the eSense algorithm to compute user's engaging attention and concentration. The eeg_ID software was used to connect the Mindwave through Bluetooth. The EEG Raw Data can be recorded in a .csv file. In addition, the signals related to Alpha Low, Alpha High, Beta Low, Beta High, Delta, Gamma Low, Gamma High and Theta frequencies can be also recorded. Based on these information, three parameters were used in this study: Fatigue [24], Stress [25] and Immersion [26].

3 Methodology Results

3.1 Clustering Methods

To achieve the objectives of our study, we organized the data using 3 different clustering methods in order to verify whether the parameters (Fatigue, Stress and Immersion) were more or less discriminative. The clusters were prepared based on Error (average number of wrong answers for each level obtained by all participants), Time (average time spent on each level by all participants) and UX (User eXperience obtained through a survey made to students to classify each level in 3 degrees of difficulty (Low, Medium, High) (Table 1).

Table 1. Clustering levels considering error, time and user experience methods

Error method		Time method		UX method	
C1_E:	L9, L14	**C1_T:**	L9, L14	**C1_UX:**	L1, L12
C2_E:	L2, L3, L10, L11, L13, L15	**C2_T:**	L2, L3, L4, L5, L6, L7, L8, L10, L11, L12, L3, L15	**C2_UX:**	L2, L3, L4, L5, L6, L8, L10, L11, L13
C3_E:	L1, L4, L5, L6, L7, L8, L12	**C3_T:**	L1	**C3_UX:**	L7, L9, L14, L15

3.1.1 Error Method

Figure 3 shows the levels and the errors made in each of them by the totality of individuals. The clustering analysis led to the formation of the following clusters: C1, consisting of the levels L9 and L14 (where individuals made more mistakes); C2 consisting of the levels L2, L3, L10, L11, L13 and L15; C3 consisting of levels L1, L4, L5, L6, L7, L8 and L12 (where individuals made no mistakes).

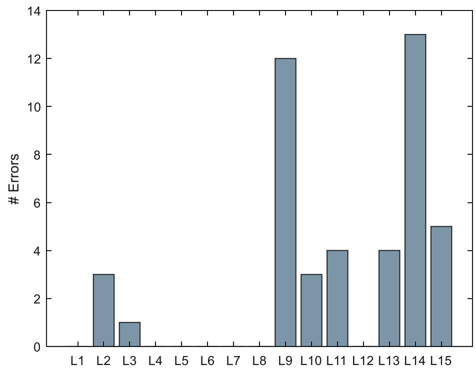

Fig. 3. Number of errors in each level for all participants

3.1.2 Time Method

Figure 4 shows each of the levels and the response time obtained in each of them by the totality of individuals. The clustering analysis by response time led to the constitution of the following clusters: C1 consisting of levels L9 and L14 (where individuals had the longest response time); C2 consisting of levels L2, L3, L4, L5, L6, L7, L8, L10, L11, L12, L13 and L15; C3 constituted by L1 (where individuals had the shortest response time).

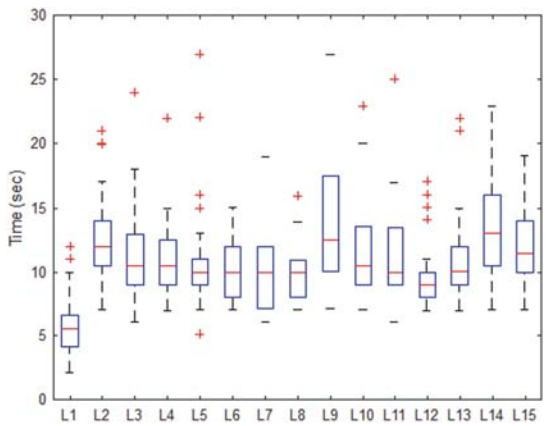

Fig. 4. Time in seconds spent for all participants in each level

3.1.3 UX Method

Figure 5 shows each of the levels and the UX classification in each of them by the totality of individuals. The clustering analysis by the three defined difficulty levels (Low, Medium, High) was the following: C1 consisting of levels L1 and L12; C2 consisting of levels L2, L3, L4, L5, L6, L8, L10, L11 and L13 and C3 consisting of levels L7, L9, L14 and L15.

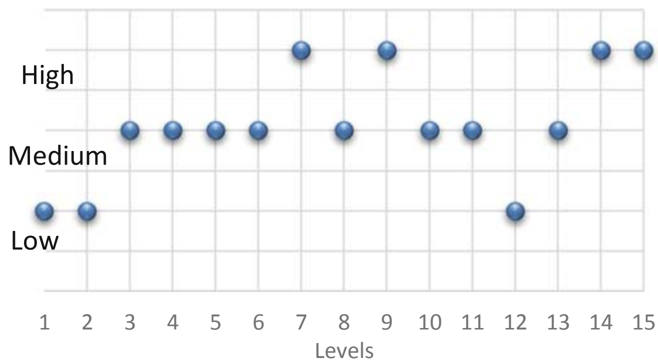

Fig. 5. Average of levels classification (Low, Medium and High) by all participants considering all levels

3.2 Features Analysis

Next the jointly boxplot for all the parameters analyzed, namely Immersion (Fig. 6), Fatigue (Fig. 7) and Stress (Fig. 8) are presented. The three different forms of data clustering were considered to compare the parameters values: Immersion, Fatigue and Stress. The main objective of this analysis is to understand the best clustering method in order to be able to discriminate the dataset. As can be seen by the figures, for all the parameters of interest, the most discriminative method is the UX method, so in the next section we will focus our analysis on this method of clustering.

Figure 8 shows that the Immersion parameter is more discriminative considering the UX and the Error methods in the data clustering. Note that for both methods there is a statistical difference between the values of each cluster and average terms considering a 90% confidence interval.

In the case of the Fatigue parameter, there are two methods that stand out, UX and Time, having the UX significant differences between all clusters (Fig. 7).

In the case of the Stress parameter, the differences between the different grouping methods are not so evident, although the UX method and the Error method can be highlighted as more discriminative.

From the general analysis, we concluded that the UX method stands out for all the considered parameters.

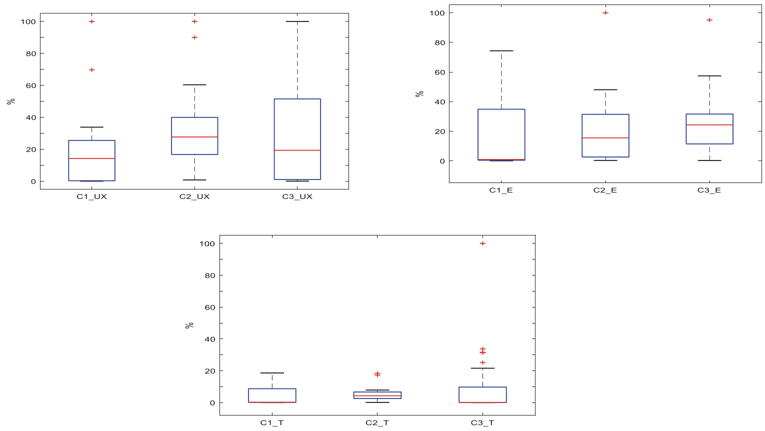

Fig. 6. Immersion values for each cluster (C1, C2 and C3) considering the three techniques of clustering: User Experience (UX), Time (T) and Error (E).

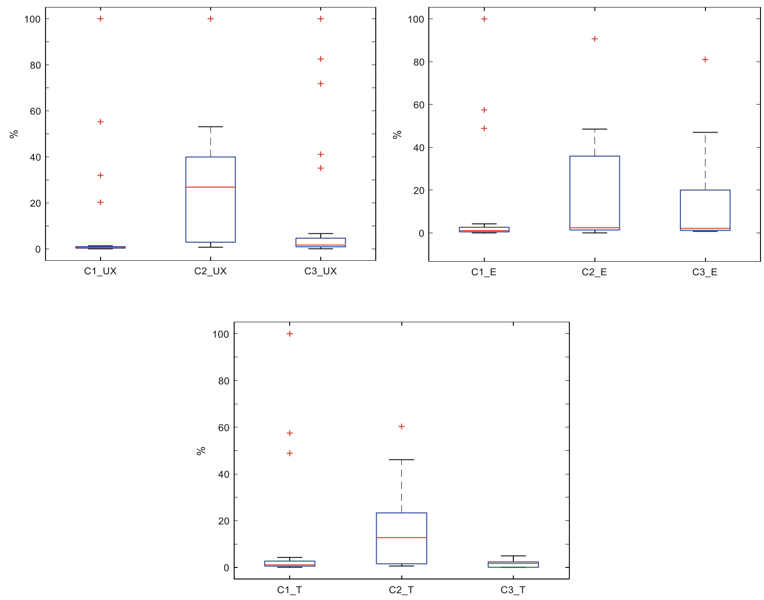

Fig. 7. Fatigue values for each cluster (C1, C2 and C3) considering the three techniques of clustering: User Experience (UX), Time (T) and Error (E).

3.3 Results Discussion

Next, the discussion of the results obtained for the organization of clustering, according to the User eXperince, will be presented. First, we observed that the average time spent in each cluster for all individuals was as follows: C1 of 7.72 s, C2 of 11.84 s and C3 of 12.48 s. We thus confirm that the lowest difficulty levels are found in cluster C1 and the

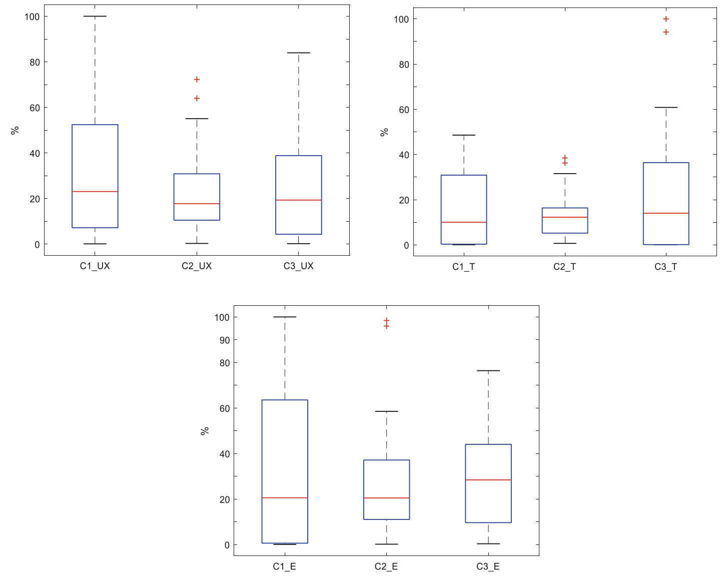

Fig. 8. Stress values for each cluster (C1, C2 and C3) considering the three techniques of clustering: User Experience (UX), Time (T) and Error (E).

most difficult levels are found in cluster C3. Calculating the T-test between each pair of clusters, it turns out that they are all different from each other, with the difference being the following C2 × C3 (H0 = 1, p = 0.0366, 90%); C2 × C1 (H0 = 1, p = 6.1 × 10–13, 90%); C3 × C1 (H0 = 1, p = 1.43 × 10–10, 90%).

Regarding Stress, the levels of Cluster C1 were, in all individuals, the ones that led to higher average levels (379.82), followed by those of cluster C3 (297.17) with the levels of cluster C2 obtaining the lowest average (291.94). The application of the T-test to ascertain the difference in means between each pair of clusters indicates that there is a difference between all, namely between C2 × C3 (H0 = 1, p = 0.62, 90%); C2 × C1 (H0 = 1, p = 0.14, 90%) and C3 × C1 (H0 = 1, p = 0.24, 90%).

Regarding Fatigue, the levels of Cluster C1 were those that, in all individuals, led to higher averages (9.51), followed by those of cluster C2 (6.50), with levels of cluster C3 obtaining the lowest average (4.08). The application of the T-test to ascertain the difference in means between each pair of clusters indicates that there is a difference between all, namely between C2 × C3 (H0 = 1, p = 0.19, 905); C2 × C1 (H0 = 1, p = 0.57, 90%) and C3 × C1 (H0 = 1, p = 0.29, 90%);

Regarding Immersion, the levels of Cluster C1 were, in all individuals, the ones that led to higher averages (165.91), followed by those of cluster C2 (101) with the levels of cluster C3 obtaining the lowest average (71.39). The application of the T-test to ascertain the difference in means between each pair of clusters indicates that there is a difference between all, namely between C2 × C3 (H0 = 1, p = 0.13, 90%); C2 × C1 (H0 = 1, p = 0.13, 90%) and C3 × C1 (H0 = 1, p = 0.0178, 90%).

The descriptive statistic of Fatigue, Immersion and Stress can be seen in Table 2, Table 3 and Table 4, respectively.

The results of the cluster analysis indicate that in cluster C1 the average response times are the lowest, meaning that it is the cluster that has the easiest levels to identify. An individual analysis shows that L1 is the one with the lowest response time, followed by

L12. These 2 levels were also correctly identified by all individuals. However, this is the cluster with the highest levels of fatigue, which means that these combinations in long periods will be avoided because they cause tiredness. The average level of immersion in this cluster is also the highest, with the same being verified in the individual analysis of each of these levels in relation to the totality of levels for all individuals, meaning combinations that lead to a good concentration.

Table 2. Clustering levels for fatigue, considering error, time and user experience method

Fatigue			
Min.	Med.	Max.	St. dv.
C1: 0.011	**C1:** 9.51	**C1:** 121.13	**C1:** 26
C2: 0.019	**C2:** 6.50	**C2:** 26.26	**C2:** 6.36
C3: 0.009	**C3:** 4.08	**C3:** 30.52	**C3:** 8.31

Table 3. Clustering levels for immersion, considering error, time and user experience method

Immersion			
Min.	Med.	Max.	St. dv.
C1: 0.36	**C1:** 165	**C1:** 954	**C1:** 215
C2: 2.63	**C2:** 103	**C2:** 319	**C2:** 75.65
C3: 0.15	**C3:** 71.39	**C3:** 255	**C3:** 17.78

Table 4. Clustering levels for stress, considering error, time and user experience method

Stress			
Min.	Med.	Max.	Std. dev
C1: 1.57	**C1:** 379.8	**C1:** 1262.8	**C1:** 341.3
C2: 3.86	**C2:** 291.9	**C2:** 912	**C2:**231.5
C3: 2.7	**C3:** 297.2	**C3:** 1060.2	**C3:** 278.7

In the C2 cluster, the average response times are higher than in the previous cluster, meaning that there are factors that make the levels more difficult to identify. In this cluster, although levels L4, L5, L6 and L8 were correctly identified by all individuals, these levels required more time to be correctly identified. The L4 is among the levels of this cluster with the highest average fatigue for all individuals, perhaps because it has a vibrant and clear background and writing colour (orange and green). According to Perron, certain contrasts create so much vibration that it diminishes readability [27, 28]. This level (L4) is similar, in general, to L2, having a combination of similar colours, but L4 has a less uniform distribution of colours in the background that can confuse the user. L5 is the level of this cluster that causes more fatigue (and the 2nd in all levels) and more immersion (and the 1st in all levels), perhaps because it has both a vibrant background and foreground colours (red and green) but is more attractive. L6 leads to less fatigue but some immersion. We can consider that this level contains the same colour combination as L4, but in a smoother and clearer way, especially with regards to the background colour. L8 despite having two light colours, they establish contrast generating high levels of immersion but also fatigue. L8 has a colour combination similar to L4 and L6 but inverted and less intense, taking a little more time to identify. L3 was not correctly identified by 1 individual and it is the level that has less immersion and the second that has less fatigue in this cluster. L3 has a less intense writing colour or with similarly coloured dots further away, taking longer to identify, but the response options may have given some clue towards the correct identification by a greater number of individuals. L2 and L10 were not correctly identified by 3 individuals, showing curiously low levels of fatigue in average terms for all individuals, but L2 shows high levels of immersion. L11 level was not correctly identified by 4 individuals, with relatively high levels of fatigue and immersion. The image shown in L11 is difficult to detect by moving away from similarly coloured dots. We can consider that L11 would have the same characteristics as L6, but the points of similar colour in the way to be detected are further apart having additionally larger points and less different colours nearby, making the task more difficult.

In the C3 cluster, response times are the highest. Levels L14 and L9 were the levels incorrectly identified by a greater number of individuals, respectively by 13 and 12 individuals as well as the levels with the highest level of fatigue in this group. Also, L15 was not correctly identified by 5 individuals. However, both this level and L7 obtained lower levels of fatigue within this cluster. In terms of immersion, and within this cluster, the levels obtained decreasing immersion values at the following levels L15, L7, L14 and L9. At the L9 level, colours with little contrast predominate and the figure to be detected has points of similar colour further away. L7 is similar to L9 but the colours are more intensified, becoming darker, perceiving better than L9 but causing more tiredness. In L14 orange over brown predominates, with little contrast. L9 and L15 are only perceived by the suggested answer.

4 Conclusions

The colour plays a key role in any graphic design of any interactive system. One of the main goals of its utilization is the readability and its correct perception in order for correct communication to occur. However, there are colour combinations that are more easily perceived and carry a message better than others while others produce visual discomfort, causing visual noise and sometimes even distorting the message that is communicated or, at least, tiring the user.

Despite growing knowledge about colour processing and understanding, it is not common to know how the brain processes the information in the presence of certain colour combinations. For that we made an experiment consisting in the identification of a certain shape in several figures having different colour combinations, using a non-conventional approach, the EEG signal. The idea was to collect several parameters not subjective or causing doubts but impossible to tamper with and getting information about the levels of immersion, stress or fatigue.

Although it was not possible to obtain a clear answer to the research questions, the study confirmed that a good chromatic contrast is essential to minimize the levels of fatigue and stress. In addition, it was found that the level of immersion can be caused either by contrasts that are difficult to perceive or by chromatic combinations that are attractive for the user.

We believe that this work represents a set of promising developments that could be very relevant in the area of HCI and with applications to many other areas.

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