

Received September 3, 2021, accepted September 21, 2021, date of publication September 23, 2021, date of current version October 6, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3115179

Assessing Footwear Comfort by Electroencephalography Analysis

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This work was supported in part by the Centro para el Desarrollo Tecnológico Industrial (CDTI), Spain, under Project IDI-20190094; "Dispositivo de Evaluación de Confort en Productos de Moda-Calzado-Confortbrain."

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Organismo Evaluador de Proyectos (OEP) of Miguel Hernández University of Elche under Reference No. DIS.JAP.02.20, and performed in line with the Helsinki Declaration.

ABSTRACT Footwear comfort is one of the determinant factors in a buyout decision. The understanding of which brain patterns are involved in the comfort perception of footwear could be an important element to develop the consumer neuroscience field, and could even help during the development phase of new products. The present paper studies the comfort perception through the electroencephalography analysis of the brain signals of ten subjects during walking. For the analysis, different features were extracted from the subject's biosignals based on power spectral density attributes and temporal and statistical parameters of the data under analysis. The research compared the features when the subjects were wearing a comfortable and a uncomfortable shoe by size on a treadmill. The results indicate that both kind of shoes could be classified with average accuracies of 84,3% and that an influence of parietal, tempo-parietal and in a minor way frontal lobes was detected. Despite the subject's dependency on the results, the research demonstrates that a common electrode and feature configuration could be applied keeping the results in an average accuracy of 83,7% and that a reduction to a 12 electrode setup maintains the accuracy at a 78,0% value.

INDEX TERMS Consumer neuroscience, comfort perception, EEG, footwear, neuro-marketing.

I. INTRODUCTION

Footwear is one of the most important fashion industries in Spain [1]. However, globalization and industry dislocation make necessary a higher inversion in R&D [2]. This could provide an extra value to the product and keep competitiveness in a high demanding sector, saving home industry [3].

The concept of consumer neuroscience, also referred as neuromarketing by some authors, is emerging as a marketing tool in the last decade [4]. Neuroscientific tools are usually applied to provide a quantitative evaluation of marketing stimuli. Therefore, they are presented as an alternative way to evaluate the response to traditional advertisements [5]. Consumer neuroscience tries to answer which are the unconscious and cognitive processes behind decision making. The tools that are used for assessing the brain activity can be based on the measurement of electrical vari-

ations or metabolic brain changes. Among the techniques that are used to detect the electrical activity changes it can be counted: electroencephalography (EEG), magnetoencephalography (MEG), steady-state topography (SST) and transcranial magnetic stimulation (TMS). For the evaluation of the metabolic brain processes, the used tools can be: functional magnetic resonance imaging (fMRI), positron emission imaging (PET) and functional transcranial Doppler sonography (fCTS). A complete review of these techniques and its applications to consumer neuroscience can be checked in [4]. In literature, some of the EEG applications are usually associated with the neural response to TV commercials [5], [6], cognitive attention in social media [7], [8] or movie-trailers prediction of commercial success [9].

The approach of the current research focuses on the product development instead of advertisement perception. Two of the most relevant aspects, beyond price and branding, a customer takes into consideration in a footwear buyout decision are design and comfort level [10]. The manuscript studies

The associate editor coordinating the review of this manuscript and approving it for publication was Sung Chan Jun¹.

the potential consumer acceptance of a product based only on the EEG assessment of comfort. This way, the research remains limited to a specific product feature, avoiding measuring different product properties which could affect the brain patterns during the decision making.

Comfort can be associated with the nature of the sole composition, the footstep mechanisms [11], or even foot morphology [12]. A bad size choice can affect the comfort perception, and it can even be the cause of plantar or finger injuries [13]. Materials, especially in the case of insoles, have also a clear impact on comfort [14].

The comfort level in footwear is usually assessed biomechanically by biometric sensors, such as sensorized pressure insoles [15]. However, there are not many studies that carry out the assessment of comfort through its correlation with electroencephalography (EEG) signals. In [16], an study of comfort for high-heeled shoes with EEG was shown. It was revealed that there was a correlation between alpha band (8-15Hz) and the size of the heel, appearing a power desynchronization the higher the heel was in occipital and parietal lobes. However, the lack of robust pre-processing techniques to address possible motion artifacts and the limited control during the experimental protocols make necessary further research. Nevertheless, EEG has been used in comfort assessment of external stimuli such as music or fragrances [17], or temperature changes [18], [19]. There are also investigations that correlate variations in beta band (16-30Hz) for high transpirable outdoorwear clothing in comparison to 100% cotton materials [20]. However, these findings have limited application to footwear comfort as the EEG patterns could be different.

The present research explores the footwear comfort perception through EEG analysis. It tries to give answer to the question if it is possible to distinguish by the analysis of EEG signals between a comfortable or an uncomfortable state when a subject is walking with different kinds of shoes in a controlled lab setup. The study also indicates which cortex areas are more determinant to both states of mind and if these dependencies are subject dependant or can be generalized to most of the subjects. During the research, 18 different indices were computed to characterize the brain patterns based on the recordings of 27 electrodes distributed on the scalp. The combinations of indices and electrodes were tested by statistical significance in order to determine which features could determine the footwear comfort perception. The results achieved up to 84,5% in average accuracy for the ten experimental subjects and indicated an influence mainly in parietal and temporal lobes and in a minor way in frontal cortex. The research entails an step up in consumer neuroscience of footwear products.

II. MATERIAL AND METHODS

A. PARTICIPANTS

Ten subjects participated in the study respecting gender ratio (men: S01-S05 with $22,4 \pm 2,1$ years old, women: S06-S10 with $21.6 \pm 0,9$ years old). They were informed about the

experiments and signed an informed consent in accordance with the Declaration of Helsinki. They did not report any known disease and had no movement impairment. All procedures were approved by the Responsible Research Office of Miguel Hernández University of Elche, Spain.

B. EQUIPMENT

EEG signals were recorded with a 32 wet slim electrode system (Brain Products GmbH, Germany). Twenty seven of the electrodes were used for collecting the brain signals of the subjects from the scalp (AF3, AF4, F5, F1, F2, F6, FT7, FC3, FC1, FCz, FC2, FC4, FT8, C3, C1, Cz, C2, C4, TP7, CP3, CPz, CP4, TP8, P5, P2, P3, P6) following the 10-10 international system on an actiCAP with 64 possible positions (Brain Products GmbH, Germany). The electrode distribution was done trying to cover the maximum number of brain zones as literature is not conclusive about the comfort location. Electrooculography (EOG) signals were registered through four of the electrodes positioned around the eyes. They were positioned in a bipolar setup to assess the ocular contribution as input to the artifact mitigation algorithm of blinking and eye motion [21]. The signals of each channel were amplified using a BrainVision BrainAmp amplifier (Brain Products GmbH, Germany), and then transmitted wirelessly to the BrainVision recorder software by a Move unit (Brain Products GmbH, Germany). Ground and reference electrodes were located in the right and left ear lobes respectively.

C. EXPERIMENTAL PROTOCOL

Each subject visited the laboratory twice. During the first day the subject was informed about the experiment. After signing the informed consent, head and foot sizes were measured in order to select the correct size of the EEG cap and the uncomfortable shoe. Subjects tried different shoe's sizes selecting one or two sizes below for the uncomfortable footwear. For the second day, subjects were instructed to use as comfortable shoes worn out sneakers they were used to. Figure 1 shows an example of footwear to be used during the experimental setup. Uncomfortable shoes were always new and the same model for all the subjects, with different sizes to assure the discomfort perception.

During the second day the subjects performed the experimental session. First, they were instrumented with the EEG equipment. In order to mitigate motion artifacts, wires were fixed by clamps and a medical mesh was placed over the cap to avoid any fluctuations of wires and electrodes. Electrode impedance was controlled to be below 30 K Ω for all the electrodes. The experimental protocol can be seen in Figure 2 and consisted of the following steps:

- First, five trials with the comfortable shoe were registered. Each of the trials was structured with the following times: 15 seconds standing still to assure the artifact filtering convergence, 15 seconds for starting and stabilizing the treadmill and 2 minutes of EEG data acquisition for analysis at a stable walking speed of 2 km/h.

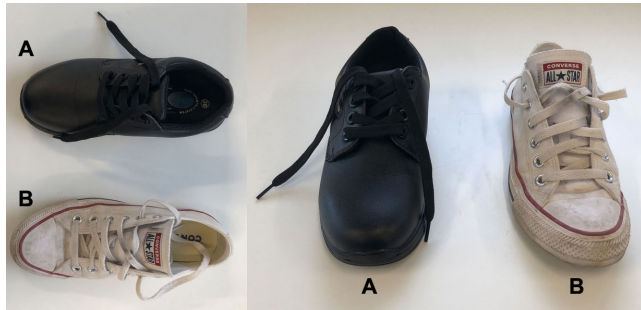


FIGURE 1. Example of footwear selection for the experimental session. Uncomfortable shoes (A) consisted of brand new industrial shoes of one or two sizes below the subject's one, while comfortable shoes (B) consisted of worn out sneakers the subjects were used to. (A) industrial footwear (EUR36/US5), (B) Converse sneakers (size EUR37/US6).

- After the first five trials, a controlled break of ten minutes was applied. Subjects sat on a chair and took their shoes off, waiting till the minute 8 for putting the uncomfortable footwear on. Times were controlled to assure that subjects had similar times of recovery.
- After the ten minutes rest, subjects sat up and went to the treadmill to start the next trial series. They consisted of five trials with the same structure of the previous trials.

Figure 3 shows two of the subjects wearing both kinds of footwear on the treadmill. The full experimental protocol was designed to not be extended beyond 2 h in order to avoid fatigue or a lack of focus by the subjects.

D. DATA ANALYSIS

The registered data were processed in several steps. Although the analysis was carried out offline, part of the pre-processing techniques were applied online as data were acquired. The next paragraphs describe the different steps followed during the data analysis.

1) HARDWARE AND PRE-PROCESSING FILTERS

Data, after being amplified by Brainamp module, were pre-processed by several filters in real time. Hardware filters were selected in the Brainvision pycorder acquisition software (Brain Products GmbH, Germany). These filters were a notch one at 50Hz, in order to mitigate the contribution of the network component in Europe, and a high-pass band filter at 0.5Hz in order to eliminate the DC component. Once filtered, data were sent by an adapted API provided by Brain products to Matlab.

Once in Matlab, H^∞ algorithm was applied sample by sample in real time to mitigate any artifact produced by blinking or eye movement [21] with the contribution of the registered bipolar electrodes placed around the eyes.

Once data were registered, two additional pre-processing filters were applied offline. A Laplacian spatial filter was executed to enhance the local activity of each electrode [22], and finally a 4th order Butterworth state-variable band-pass filter between 5-40Hz allowed to increase the signal to noise ratio

TABLE 1. List of features used for brain status characterization. Definition of the considered EEG rhythms can be consulted in table 2.

	Feature
1	$\sum \beta / \sum (\theta + \alpha)$
2	$\sum \beta / \sum \alpha$
3	$\max(\theta + \alpha) / \sum (\text{total})$
4	$\max(\alpha) / \sum (\text{total})$
5	$\max(\beta) / \sum (\text{total})$
6	$\sum (\theta + \alpha) / \sum (\text{total})$
7	$\sum (\alpha) / \sum (\text{total})$
8	$\sum (\beta) / \sum (\text{total})$
9	$\max(\alpha)$
10	$\max(\beta)$
11	$\max(\text{total})$ [Yule Walker]
12	$std_j = \sqrt{\frac{1}{N-1} \sum_{i=1}^N x_{ji} - \mu_j ^2}$
13	$E_j = \sum_{i=1}^N x_{ji}^2$
14	$W E_j = \text{wentropy}(x_j, \text{'log energy'})$
15	Weibull parameter (scale)
16	Hjörth parameter (activity)
17	Hjörth parameter (mobility)
18	Hjörth parameter (complexity)

x : EEG signal; i : sample; N : samples per epoch; j : channel; μ : EEG mean of an epoch. For bands definition check Table 2.

before further processing, filtering any motion components caused by walking and the power line interference (50 Hz in Spain).

2) FEATURE EXTRACTION

For characterizing the brain patterns of the individuals during the walking times, different indices were computed. As there is not a clear conclusion in literature about the patterns that allow the distinction between comfort and discomfort, 18 indices covering different frequency bands relationships and statistical and temporal features were defined. The choice of the indices was based on our previous study in [23]. Some of the non-relevant indices of former research, such as the ones based on Hilbert transform, were neglected for this one due to their lack of influence on the results. Table 1 sums up them.

The different features were computed in epochs of 5 seconds without shifting. Different epoch sizes were preliminary tested for accuracy, considering all the electrodes and features for the classifiers, determining 5 seconds as an optimum length for analysis. This way, each register under analysis consisted of 2 minutes of data with a total of 24 epochs per register and channel. Each class (comfort or discomfort) reached an amount of 120 data vectors per subject (24 epochs \times 5 trials) with a possible length of 1 to 486 characteristics depending on the groups of features and electrodes to consider (27 channels \times 18 features). The different features are described in the following paragraphs.

α : POWER SPECTRAL DENSITY (PSD) FEATURES (1-11)

Features 1-10 were computed using the power spectral density (PSD) by Burg's method using Matlab's function *pburg*. A 18th order autoregressive model with a 0.5Hz step was applied between 0-50Hz for extracting the spectral information. As the signals were pre-filtered between 5-40Hz,

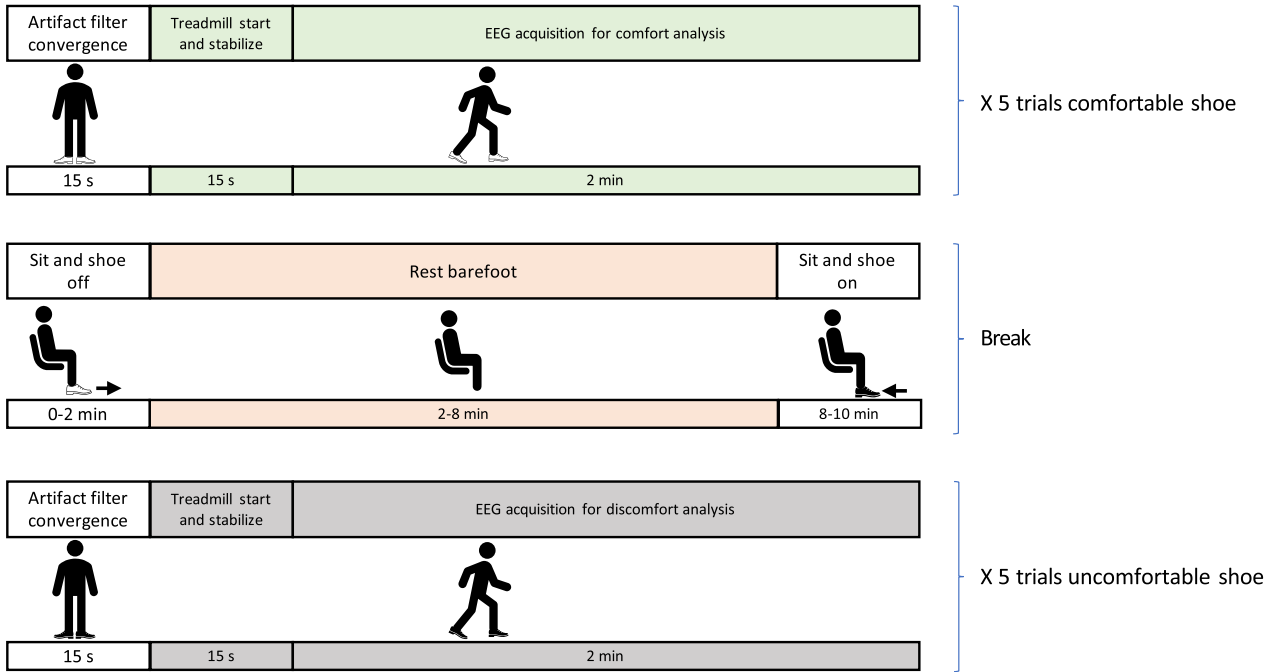


FIGURE 2. Structure of the experimental session. A session consisted of two blocks of 5 trials for each kind of footwear, separated by a controlled resting break for shoe changing.



FIGURE 3. Configuration during the EEG acquisition on the treadmill. The EEG cap wires were attached with clamps and a medical mesh. Output signals were transmitted wirelessly by the move unit placed on the waist. (A) Subject S10 using uncomfortable shoes (EUR40/US9 the comfortable size was EUR41/US10); (B) Subject S03 wearing his comfortable sneakers (EUR43/US10).

as indicated in section II-D1, PSD contained the spectral information of these frequencies. In order to contrast another PSD method, feature 11 used the Yule Walker’s method with a 3rd order model for the whole pre-filtered band using *pyulear* function in Matlab. Features 1-10 were based on the relationships between rhythms or their maximum value (see Table 2 for the rhythm’s definition). Table 1 indicates the band considered for PSD computing for each feature. This can consider the total PSD for the band or the maximum value per epoch depending on the feature.

TABLE 2. Frequency bands of the considered EEG rhythms for analysis. Note that θ band starts at 5Hz due to the pre-filtering instead of the usual 4Hz and that total band includes low gamma band (30-40 Hz) which was not analyzed on its own.

Rhythm	Band (Hz)
Theta (θ)	5-7
Alpha (α)	8-14
Beta (β)	15-30
total	5-40

b: TEMPORAL AND STATISTICAL FEATURES (12-18)

EEG deviation (feature 12) measures the standard deviation of the EEG signal of a channel regarding its mean μ . Feature 13 represents the EEG energy of the signal for the total band. Feature 14 uses the Matlab’s wavelet function *wentropy* to compute the log energy entropy of the epoch. See Table 1 for more details.

Features 15-18 represent an statistical analysis of the epoch samples of each channel. Feature 15 uses the *wblfit* Matlab’s function to obtain the scale parameter of the signal, while features 16-18 represent the normalized slope descriptors of Hjörth [24], [25]: activity, mobility and complexity. Activity represents the variance of amplitude in time, mobility represents the mean frequency or the proportion of standard deviation of the power spectrum, and complexity the similarity of the signal’s variation to a pure sine wave.

3) STANDARDIZATION

In order to have a similar weight for each of the features, their value were standardized by feature and electrode for each

subject. For this purpose, the function *normalize* of Matlab was used. It returns the vectorwise z-score of each feature per electrode with center 0 and standard deviation 1.

4) CLASSIFICATION

Different groups of electrodes and features were considered for analysis. This means that the vectors representing the brain patterns of each 5 seconds epoch could vary in their size, depending on the number of features and electrodes chosen for the analysis, from 1 column (1 feature of 1 electrode) to 486 columns (18 features of 27 electrodes). A leave-one-out cross validation of the data was carried out using 4 trials of each class as model (4 trials \times 24 vectors = 96 vectors per class) leaving one register out for assessing the accuracy of the classifier (24 vectors per class). The pairing of the classes was done based on the order of the trials. This means that for testing trial 3 of each class, the model consisted of trials 1-2 and 4-5 of both classes. The results showed in the tables of section III represent the averaged accuracy classification of the 5 trials cross validation of the two classes. In the study, two different classifiers were considered using the Matlab functions: *knn_classifier* for K-nearest neighbours (KNN) [26] and *fitsvm* for Support Vector Machine (SVM) [27].

III. RESULTS

This section provides the results of the accuracies in the classification of the 24 epochs of each register for both classes (comfort and discomfort). The results are averaged per class for all the registers using the cross validation (24 epochs \times 5 trials). The research is applied in several steps. First, all the features and the electrodes are tested to evaluate the behaviour of different classifiers and kernels. Once the best classifier is chosen, a statistical study is accomplished to select the features of each electrode that could have an influence in the differentiation of both classes. After determining the most relevant features and electrodes, the accuracies are computed again for different classifier models. These models are based on different selections of features and electrodes depending on their common presence in a certain number of subjects or even personalizing them by subject. Finally, a statistical study is done to check the dependency for four of the chosen classifier models on: gender, subject and type of footwear.

A. CLASSIFIER COMPARISON

The first analysis compares the performance of the chosen classifiers for different parameters. The input vectors considered all the features and electrodes, which meant a 486 size vector per epoch.

1) KNN

A sweep of the K value was carried out for odd values from $k = 1$ to 61. Figure 4 shows the average value with its standard deviation for the global accuracy of both classes for all the subjects, following the cross validation explained before.

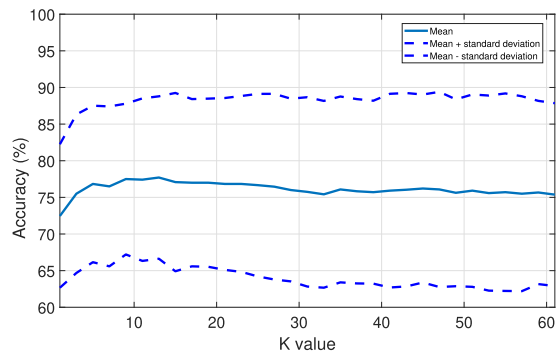


FIGURE 4. Average accuracy in the classification of both classes for the 10 subjects depending on the K value of the KNN classifier. The results were usually over the 75% accuracy. The optimum result with lowest deviation was achieved for $k = 9: 77,5 \pm 10,3\%$.

The optimum value with lowest deviation was achieved for $K = 9$, being the average accuracies for the vector tests usually over 75%.

2) SVM

Three different functions were tested for the SVM classifier: linear, polynomial and gaussian. The hyperparameter optimization of the model was checked obtaining similar results to the default parameters, so default Matlab parameters were used. However, the type of function did have an effect on them. The average value for the global accuracy of both classes achieved just a $55,4 \pm 9,2\%$ for the polynomial and a $51,9 \pm 4,2\%$ for the Gaussian functions, while the linear kernel reached a $84,3 \pm 10,8\%$. Table 3 shows a comparison between the SVM linear and KNN-9. As the best results were obtained by the SVM-linear classifier the rest of the study used this classifier.

B. ELECTRODE AND FEATURE INFLUENCE

Previous results considered the 27 electrodes and 18 features. Although average results for the SVM classifier achieved a 84,3% accuracy, further analysis was needed in order to detect which brain lobes (electrode position) and features were more important in the characterization of comfort vs. discomfort perception based on the EEG signals. A selection of the determinant characteristics could also reduce the size of the vectors used in classification. With this objective, a Mann-Whitney U test [28], also known as Wilcoxon rank sum test, was applied for each feature and electrode in order to detect which of them were significantly different ($p = 0.05$) in the comparison between both classes. The reason of choosing a non-parametric test such as the Mann-Whitney U was to be conservative in case data did not follow a normal distribution. Figure 5 indicates which significantly different features and electrodes were common for different number of subjects.

The SVM-linear classification was executed again, selecting those features and electrodes that were common for different number of subjects and by each individual subject (models personalized by subject). The average classification

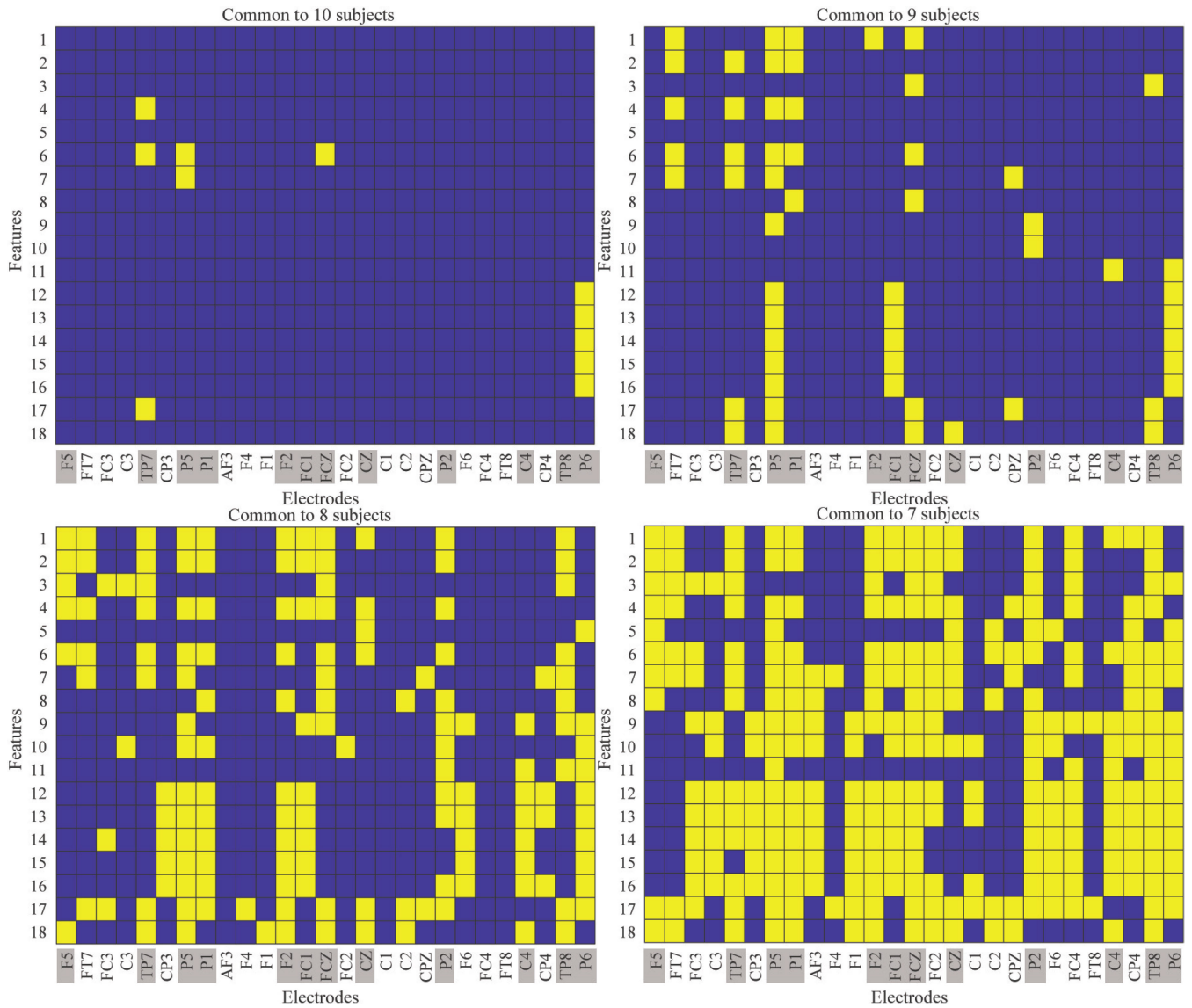


FIGURE 5. Features per electrode significantly different in the class comparison. The image shows which of them were common for 10, 9, 8 and 7 subjects in yellow. Relevant electrodes appear in grey.

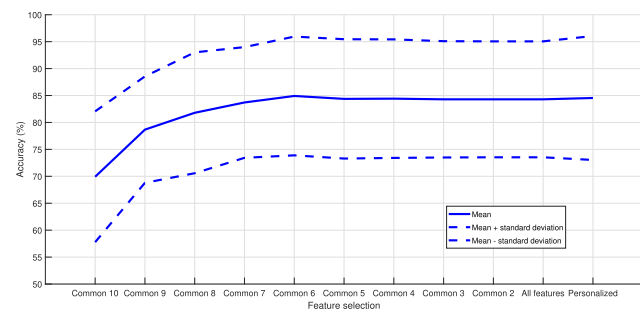


FIGURE 6. Accuracy of the SVM-linear classifier depending on the common group of features and electrodes considered (see figure 5). Although the maximum value was achieved for 6 subjects, 7 was chosen as a compromise.

can be seen in Figure 6. The average maximum accuracy was achieved for the group common to 6 subjects. However, as the common group 7 had a similar value and could reduce the

number of features used (from 486 to 285), it was chosen as a compromise. A reduced number of electrodes and features allow an easier analysis of the results and correlation with the brain areas to be appointed as important in the comfort vs. discomfort characterization.

A comparison among the classifications obtained by the group of features and electrodes that were common to at least 7 subjects and those personalized by subject can be seen in Table 4. The results indicate that, although the total accuracy is higher for the personalized selection of features and electrodes (84.5 vs. 83.7 %), the balance among classes and the average deviation is generally lower for the vectors common to 7 subjects.

C. BRAIN AREA INFLUENCE

Previous subsection shows how a common selection of features and electrodes still has a high accuracy in the

TABLE 3. Accuracy comparison of KNN-9 and SVM-linear classifiers. Results show the average value for the cross validation of the 24 epochs of each trial per class and subject.

KNN-9 class accuracy (%)			
Subject	Comfortable	Uncomfortable	Total
S01	80,8 ± 11,3	61,7 ± 11,6	71,3 ± 6,3
S02	78,3 ± 19,0	61,7 ± 18,7	70,0 ± 4,3
S03	92,5 ± 9,0	87,5 ± 8,3	90,0 ± 5,8
S04	86,7 ± 12,3	80,0 ± 15,4	83,3 ± 11,8
S05	93,3 ± 6,3	87,5 ± 9,3	90,4 ± 6,7
S06	78,3 ± 32,7	71,7 ± 9,9	75,0 ± 16,1
S07	62,5 ± 38,8	77,5 ± 17,8	70,0 ± 22,2
S08	63,3 ± 20,9	75,8 ± 4,6	69,6 ± 11,1
S09	82,5 ± 8,5	90,8 ± 6,2	86,7 ± 3,2
S10	53,3 ± 30,2	84,2 ± 12,3	68,8 ± 15,4
Average	77,2 ± 18,9	77,8 ± 11,4	77,5 ± 10,3

SVM-Linear class accuracy (%)			
Subject	Comfortable	Uncomfortable	Total
S01	84,2 ± 12,3	87,5 ± 8,8	85,8 ± 9,9
S02	75,8 ± 13,0	79,2 ± 7,8	77,5 ± 5,0
S03	99,2 ± 1,9	98,3 ± 2,3	98,8 ± 1,1
S04	81,7 ± 18,3	86,7 ± 14,6	84,2 ± 10,7
S05	94,2 ± 5,6	90,8 ± 9,9	92,5 ± 5,2
S06	76,7 ± 37,3	96,7 ± 3,5	86,7 ± 18,2
S07	78,3 ± 22,5	65,0 ± 37,2	71,7 ± 24,5
S08	74,2 ± 26,7	78,3 ± 12,6	76,3 ± 13,9
S09	90,0 ± 10,5	94,2 ± 9,1	92,1 ± 4,8
S10	64,2 ± 36,2	90,8 ± 12,3	77,5 ± 14,3
Average	81,8 ± 18,4	86,8 ± 11,8	84,3 ± 10,8

TABLE 4. Accuracy (%) for the classification of comfortable and uncomfortable footwear using the features and electrodes common to at least 7 subjects and personalized by subject.

Common to 7 subjects accuracy (%)				Vector size
Subject	Comfortable	Uncomfortable	Total	
S01	83,3 ± 10,6	84,2 ± 13,0	83,8 ± 9,0	285
S02	69,2 ± 24,4	74,2 ± 16,2	71,7 ± 8,4	
S03	99,2 ± 1,9	95,0 ± 4,6	97,1 ± 2,8	
S04	82,5 ± 11,9	84,2 ± 18	83,3 ± 11,2	
S05	95,8 ± 4,2	92,5 ± 6,8	94,2 ± 5,0	
S06	80,0 ± 27,5	95,0 ± 4,6	87,5 ± 12,3	
S07	73,3 ± 26,9	66,7 ± 40,1	70,0 ± 26,5	
S08	76,7 ± 22,7	81,7 ± 11,3	79,2 ± 12,2	
S09	92,5 ± 7,5	92,5 ± 10,4	92,5 ± 2,4	
S10	68,3 ± 33,9	87,5 ± 13,5	77,9 ± 13,0	
Average	82,1 ± 17,2	85,3 ± 13,8	83,7 ± 10,3	

Personalized by subject (variable data vectors) accuracy (%)				
Subject	Comfortable	Uncomfortable	Total	data vector size
S01	85,0 ± 10,9	91,7 ± 6,6	88,3 ± 8,1	363
S02	69,2 ± 28,2	80,8 ± 9,6	75,0 ± 12,7	323
S03	99,2 ± 1,9	99,2 ± 1,9	99,2 ± 1,1	234
S04	84,2 ± 16,5	87,5 ± 13,5	85,8 ± 9,6	376
S05	95,8 ± 5,9	90,0 ± 11,3	92,9 ± 5,6	402
S06	77,5 ± 37,3	96,7 ± 3,5	87,1 ± 18,1	357
S07	75,0 ± 23,8	72,5 ± 41,3	73,8 ± 28,3	306
S08	69,2 ± 24,2	80,0 ± 9,5	74,6 ± 9,7	270
S09	87,5 ± 15,3	93,3 ± 9,6	90,4 ± 6,0	326
S10	67,5 ± 37,0	89,2 ± 10,0	78,3 ± 15,8	318
Average	81 ± 20,1	88,1 ± 11,7	84,5 ± 11,5	

identification of the comfort of the footwear based only on the brain signals (83.7 %). The current subsection focuses on the electrode location of those channels that had significantly different features per class, being common to different subjects.

Table 5 indicates the number of subjects that have significantly common features for a certain electrode. It is calculated

TABLE 5. Number of subjects with common significantly different features based on a Mann-U-Whitney test depending on the electrode and the number of common features. The chosen relevant electrodes appear in bold text and the rules for selecting them are color coded from red to yellow in order of relevancy.

Electrode	Common features	
	≥ 10	≥ 5
F5	7	8
FT7	6	9
FC3	7	7
C3	6	7
TP7	7	9
CP3	6	8
P5	9	9
P1	8	9
AF3	6	7
AF4	6	6
F1	6	7
F2	8	8
FC1	7	9
FCZ	8	9
FC2	7	7
CZ	7	8
C1	4	7
C2	6	7
CPZ	6	7
P2	8	8
F6	6	8
FC4	7	7
FT8	5	6
C4	7	8
CP4	7	7
TP8	8	8
P6	8	10

for a different number of common features (≥10 and ≥5). Take notice, that it just identifies those significantly common features following the Mann-U-Whitney test described in subsection III-B. Therefore, this selection of features has to be corroborated by the accuracy % obtained by the cross validation test afterwards.

Nevertheless, in order to use the information provided by Table 5, a rule of selection must be followed. The objective was to limit the number of EEG channels to 12. This could limit the costs of acquisition to a 16 electrode setup (4 for EOG and 12 for EEG) and the size of the data vectors. The process was taken in order by the electrodes that presented a higher number of subjects and common features. First, the electrodes that had ≥10 relevant common features for ≥8 subjects were chosen (P5 for 9 subjects in red and P1, F2, FCZ, P2, TP8 and P6 for 8 subjects in orange, Table 5). Then, as only seven channels passed the threshold, the process was repeated for ≥7 subjects. As the number of electrodes that accomplish this was nine, and only five new channels were required, the ≥5 relevant common features threshold was used in order to broke the tie and complement the five resting electrodes (F5, TP7, FC1, CZ and C4 in yellow, Table 5). Figure 7 shows the distribution of the chosen electrodes on the scalp following the 10-10 international system.

The reduction in size of the data vector when using 12 EEG electrodes instead of the 27 was from 285 to 154 for the features common to 7 subjects. Table 6 shows the

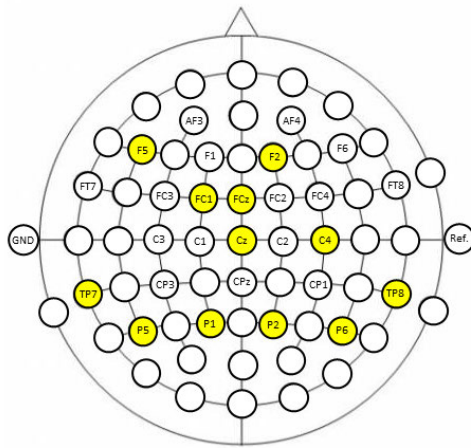


FIGURE 7. Electrodes chosen as the more relevant for the classification of comfort vs. discomfort perception of footwear.

TABLE 6. Accuracy (%) for the classification of comfortable and uncomfortable footwear using the features and electrodes common to at least 7 subjects and personalized by subject when using the 12 most relevant electrodes, see figure 7.

Subject	Common to 7 subjects accuracy (%)			Vector size
	Comfortable	Uncomfortable	Total	
S01	80,0 ± 14,8	75,8 ± 19,0	77,9 ± 10,8	154
S02	65,8 ± 21,1	66,7 ± 9,8	66,3 ± 14,2	
S03	75,0 ± 27,8	85,8 ± 9,6	80,4 ± 13,6	
S04	84,2 ± 12,3	85,8 ± 14,6	85,0 ± 10,6	
S05	87,5 ± 15,6	90,0 ± 8,6	88,8 ± 7,9	
S06	75,0 ± 37,3	90,8 ± 8,0	82,9 ± 16,2	
S07	89,2 ± 11,6	68,3 ± 29,1	78,8 ± 17,8	
S08	65,0 ± 18,3	74,2 ± 16,2	69,6 ± 9,2	
S09	80,8 ± 20,5	81,7 ± 14,0	81,3 ± 9,3	
S10	53,3 ± 32,2	84,2 ± 15,1	68,8 ± 20,4	
Average	75,6 ± 21,2	80,3 ± 14,4	78,0 ± 13,0	
Subject	Personalized by subject (variable data vectors) accuracy (%)			data vector size
	Comfortable	Uncomfortable	Total	
S01	79,2 ± 15,3	83,3 ± 14,4	81,3 ± 9,2	172
S02	67,5 ± 21,9	69,2 ± 10,9	68,3 ± 15,3	161
S03	76,7 ± 22,7	84,2 ± 9,5	80,4 ± 7,0	103
S04	80,0 ± 9,9	87,5 ± 14,1	83,8 ± 6,8	180
S05	93,3 ± 8,6	86,7 ± 13,0	90,0 ± 7,0	185
S06	76,7 ± 36,5	90,0 ± 9,6	83,3 ± 15,7	174
S07	87,5 ± 10,6	62,5 ± 35,5	75,0 ± 18,4	138
S08	61,7 ± 23,6	71,7 ± 19,9	66,7 ± 14,1	111
S09	73,3 ± 24,8	82,5 ± 13,6	77,9 ± 11,5	178
S10	63,3 ± 27,9	83,3 ± 19,1	73,3 ± 17,9	156
Average	75,9 ± 20,2	80,1 ± 16,0	78,0 ± 12,3	

accuracy results for these features and their comparison to the personalized by subject models. Accuracy drops to 78% for both common 7 and personalized features, which is still an acceptable value for the average classification of both classes.

D. STATISTICAL ANALYSIS OF THE RESULTS

The accuracies obtained per trial were analyzed statistically in SPSS [29] for four different classifier models. They corresponded to the models based on 27 and 12 electrodes using the features common to 7 subjects and personalized by subject, whose average results have been shown in tables 4 and 6. They will be called from now on as Acc_7^{27} , Acc_p^{27} , Acc_7^{12} and Acc_p^{12} depending on the number of electrodes used (27 or 12) and selection of features (common to 7 subjects

or personalized p). First, a Kolmogorov-Smirnov test of normality was checked [30], revealing a clear deviation of the normality assumption for the four models ($D(100) = [0, 790 - 0, 872], p < 0, 05$). As normality assumption was not accomplished, the analysis of the accuracy of the classifiers depending on gender, subject and footwear was based on non-parametric tests.

Mann-Whitney U test was used for binary variables. Gender influence did not show significant differences for the models Acc_7^{27} : $U = 1180, 0, z = -0, 49, ns, r = -0, 05$; Acc_p^{27} : $U = 1050, 0, z = -1, 40, ns, r = -0, 14$; Acc_7^{12} : $U = 1196, 5, z = -0, 37, ns, r = -, 04$ and Acc_p^{12} : $U = 1153, 0, z = -0, 672, ns, r = -0, 07$.

The accuracies in the classification of each kind of footwear were also studied statistically. It was revealed that both classes performed with no significant differences, being the Mann-Whitney U test statistical parameters: Acc_7^{27} : $U = 2468, 500, z = -0, 394, ns, r = -0, 04$; Acc_p^{27} : $U = 2379, 5, z = -1, 02, ns, r = -0, 10$; Acc_7^{12} : $U = 2460, 0, z = -, 45, ns, r = -0, 05$ and Acc_p^{12} : $U = 2448, 5, z = -0, 53, ns, r = -0, 05$.

Subject’s dependency is usual in EEG analysis due to different expertise or EEG illiteracy [31]. In order to check it, a Kruskal-Wallis test was done, detecting that there were significant differences by subjects, even when common features were used: Acc_7^{27} : $H(9) = 25, 12, p < 0, 05$; Acc_p^{27} : $H(9) = 29, 22, p < 0, 05$; Acc_7^{12} : $H(9) = 17, 48, p < 0, 05$; and Acc_p^{12} : $H(9) = 16, 48, p < 0, 05$ with Monte Carlo significance. As degrees of freedom was 9, individual differences were not checked by post hoc tests for all the possible combinations, but with a boxplot representation as Figure 8 shows.

IV. DISCUSSION

A. STUDY LIMITATIONS

The manuscript presents a novel study of the footwear comfort perception based on EEG. Nevertheless, it is important to remark that it is a preliminary study with some limitations. The database is formed by young subjects, five men ($22,4 ± 2,1$ years old) and five women ($21,6 ± 0,9$ years old). This makes a homogeneous demographic database with similar footwear preferences, mainly sneakers, which was something desirable for a common control of the experimental conditions, but it makes hard to extrapolate the results for other demographic profiles with different preferences. Nevertheless, the main purpose of the research was to study if footwear comfort perception could be differentiated by EEG patterns, so the number of subjects is enough for a preliminary analysis. However, an extended number of subjects with varied ages and footwear preferences would be interesting for an extended study of the human perception of footwear comfort.

B. CLASSIFIER PERFORMANCE

Results indicated that SVM classifier with linear kernel performed with higher accuracy than KNN and other SVM

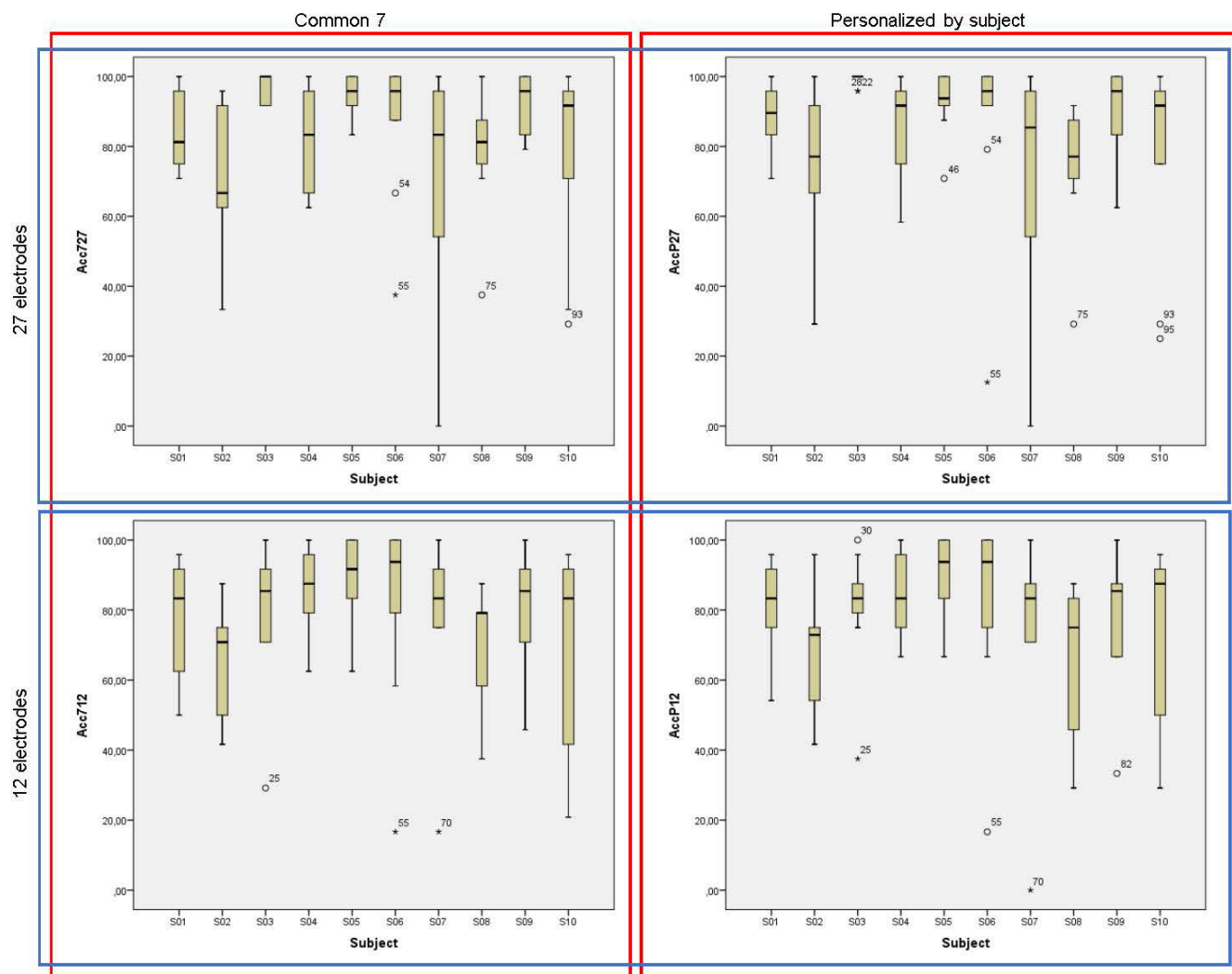


FIGURE 8. Boxplots of the accuracies of the four models under statistical study.

kernels, so all the discussion will be related to the outputs obtained by this classifier. The rest of the section will focus on the discussion of the influence caused by the subject, type of model, relevant brain zones that affect a correct differentiation between the comfort status and which features are more important.

C. SUBJECT AND MODEL INFLUENCE

The boxplots in figure 8 show the median instead of mean, which is a good way to check the data dispersion. Most of the subjects showed for the four models that the upper tail had higher accuracies and lower dispersion than the lower tail, which showed a higher dispersion (shorter whiskers and higher median than mean). Globally, subjects S02 and S08 were the ones that had the lowest results. S10 showed a high dispersion, especially for the 12 electrode models. This is mainly due to the differences between comfortable and uncomfortable accuracies shown by these subjects. This indicates that, although in general the behavior of the models was not significant different for the classes, it was for certain

subjects. This way S06, S08 and S10 showed lower comfortable accuracies than for uncomfortable, and the opposite happened for S07. This was the cause of the higher dispersion and outliers in the lower tail of these subjects.

D. BRAIN AREA INFLUENCE

The literature that analyzes the footwear comfort through EEG is limited. In Luo et. al [16] is claimed that “the differences between the standing and walking states after comparison and analyses show that in the parietal region, frontal region, and occipital region, the α value of the standing state is greater than that of the walking state”. In the same manuscript is indicated that “The α wave indices related to the comfort are regarded as a fast wave, which is most obvious in the parietal and occipital regions of the brain”. However, the comfort vs. discomfort in the paper is treated as a standing vs. walking status, which could be masking the comfort perception with the usual desynchronization during walking [32]. Nevertheless, the fact that it is appointing mainly to parietal and occipital regions and in a minor way

to frontal and temporal lobes, instead of motor cortex, provides a comparison point with our research. As section III-C (specifically Table 5 and Figure 7) indicated, the electrodes that showed more significantly different features were clearly in the parietal and temporal region. They also revealed an influence by some frontal electrodes F5 and F2. Additionally, primary cortex and somatosensory areas were also present in FC1, FCz, Cz and C4 electrodes. This could be related to differences in the gait due to the discomfort. Occipital electrodes were not considered in our research as they are more susceptible to motion artifacts. As the research in [16] did not apply any technique to mitigate motion artifacts and the comparison included a rest vs. motion analysis, it is hard to assure that the influence of occipital region in footwear comfort is determinant, and not due to differences caused by actual motion. It is important to remark that our research compares two motion states using different types of footwear, so although the experimental setup was different, results appoint to common regions that the ones indicated in [16]. Therefore, it can be stated that comfort vs. discomfort perception differences in our research can be found mainly in parietal and temporal regions and in a minor way in frontal lobe.

E. RELEVANT FEATURES

As indicated before by Luo et. al [16], the differences of comfort vs. discomfort were mainly found in α band. Our approach swept several bands and features as Table 1 showed. The common to 7 selection (Figure 5) covers lots of features for the 12 electrodes chosen as relevant. Thus, it is easier to check the more restrictive common images. For instance, in common to 10 selection (Figure 5) only four relevant electrodes had common features for all the subjects (TP7, P5, FCz and P6), being feature 6, which combines θ and α properties, common in three of the electrodes. Features 5, 8 and 10, which were related to β band, had poor relevance in 8-10 subject combinations, while temporal and statistical features were present more notoriously in parietal lobe for the 12-16 features and tempo-parietal and parietal lobes for 17-18 features. Summing up, the more relevant features in frequency were present in α band which corroborates previous studies that associated it with plantar stress, blood circulation and motion fatigue [16]. The research results also indicate an influence of θ band and statistical and temporal parameters associated with the wave shape variation.

V. CONCLUSION

The research has shown a novel analysis of the footwear comfort perception based on EEG. The lack of reports in the literature on the topic makes this research an interesting milestone in the analysis of footwear products, which could be an important first step on consumer neuroscience of these goods.

The analysis of the brainwaves of 10 subjects indicates that is possible to differentiate between comfort and discomfort perception just by EEG analysis during walking. Despite the usual subject's dependency on EEG analysis, and reported

% of EEG illiteracy that can achieve up to the 53.7% in the case of motor imagery [31], the research has shown that it is possible to create a common classification model with an average accuracy of footwear classification of 83,7% with 8 of the 10 subjects over the 75% global accuracy.

The brain areas related to comfort vs. discomfort perception can be located basically on tempo-parietal, parietal and frontal lobes for α band, fact that is consistent with previous studies. In the current research θ band resulted relevant too, and the models were improved by the use of additional statistical and temporal parameters. Nevertheless, further study is needed in order to define which are the frequency rhythms and characterizing parameters that are more relevant specifically by different brain areas.

Future research will expand the number of subjects to check the statistical validation of the conclusions. Besides, it will explore the addition of new comfort or discomfort classes, in order to corroborate that they can be classified correctly based on previously trained blind models and rate different levels of dis/comfort.

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