# Review Dry and Non-contact EEG Electrodes for 2010-2021 years

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**Abstract**
The basis of the work of electroencephalography (EEG) is the registration of electrical impulses from the brain or some of its individual areas using a special sensor/electrode. This method is used for the treatment and diagnosis of various diseases. The use of wet electrodes in this case does not seem viable, for several well-known reasons. As a result of this, a detailed analysis of modern EEG sensors developed over the past few years is carried out, which will allow researchers to choose this type of sensor more carefully and, as a result, conduct their research more competently. Due to the absence of any standards in the production and testing of dry EEG sensors, the main moment of this manuscript is a detailed description of the necessary steps for testing a dry electrode, which will allow researchers to maximize the potential of the sensor in the various type of research.

**Keywords**: EEG review; dry EEG; dry EEG electrode; dry electrode; electroencephalography; non-contact electrode EEG

## 1. Introduction

Electroencephalography is a method of studying brain functions, based on the electrical impulses from their neural origins. Cohen, M. et al. [62] wrote about how electroencephalography (EEG) played an important role in the discovery of cognition, brain function, and the prospects for this direction. The main problem in reading the EEG signal by non-invasive methods is the presence of noise and artifacts. As a result, pattern recognition with EEG is often challenging due to the low signal-to-noise ratio. Aihua, Z. et al. [44] and Zhang, A. et al. [54] explained cardiac artifacts, Wiese, S. et al. [l46] and Besio, W. et al. [47] examined the artifacts that occur when the electrodes were poorly connected. The influence of the environment on the electrode signal was considered by Biswas A. et al. [48], muscle artifacts considered Chen, X. et al [49] and Richer, N [50] and eye movement artifacts, the most popular artifacts, presented in papers [69]. To solve this problem, a few researchers started to process EEG signals by neural networks [70, 71, 72]. But neural networks require a lot of dataset and computing power and despite this the neural networks are increasingly being used in various fields of activity, robot control [73, 74] to identify various mental illnesses [51]. Over the past few years, the number of studies that have involved machine learning and deep learning models to recognize the EEG signal has significantly increased. For example, Amorim et al. [1], Acı, I. et al. [2], Amin, H.. et al. [3] used machine learning to search for artifacts in the signal in the brain-computer interface (BCI) studies. Nowadays, one application is use neural networks with EEG to help the diagnosis of diseases, for example, Alzheimer's disease. The easiest way to read the EEG signal is to use dry electrodes, what demonstrated in their work Kappel, S. et al. [51] and Damalerio, R. et al. [52]. But due to many different types of electrodes, it is not easy to understand which one is better to use. For this reason, the task of this research is to analyze progress in development in EEG sensors field.

For the EEG recordings, various sensors can be used: wet, dry, and non-contact. Most used wet sensors with low impedance, which usually varies within 200 kOhm before the application of the gel and within 5 kOhm after the application of the gel [55, 56]. But these sensors are more suitable for laboratory research. The main disadvantage is an inconvenience. For example, setting up takes much time with wet EEG sensors. Participants need to clean the hair before starting to measure EEG. Also, the change in impedance over time due to physiological changes in the gel. At the same time, if some noise can be filtered out either by a person or by a program during the diagnosis of a disease, then in terms of machine learning, a neural network can take the slightest noise as a useful signal, which in the end will lead to a false result. Machine learning is powerful instrument but still makes mistakes, so to improve the signal-to-noise ratio of EEG, for measure EEG signal needs sensors with low noise because ECG signal is weak and sensitive to interference.

Lopez-Gordo, M. et al. [4], Molinas et al. [75], Xu et al. [76] and Chi et al. [77] – presented review dry EEG sensors. However, their study did not use a systematic approach so that the complete picture of the applications of the dry electrodes is unclear. In this paper we reviewed dry and non-contact sensors for EEG measurements. We included studies in which the test results of dry and non-contact EEG sensors presented, with impedance not more than 50 KΩ, since at a given impedance value it is possible to read the EEG signal [57,58]. **S**earch for articles by keywords was carried out directly on the websites in the following publishers: Elsevier (http://www.elsevier.com/), Taylor & Francis (https://www.tandfonline.com/), Springer (https://www.springer.com/), Wiley (https://www.wiley.com/), IEEE (https://www.ieee.org/), Informa (https://www.informa.com/), MPDI (https://www.mdpi.com/), Hindawi (https://www.hindawi.com/). Keyword searches performed on the Google search engine and (https://www.researchgate.net/), (https://www.academia.edu/), Publons (https://publons.com/) mostly over the past 11 years. We used the following keywords in various combinations for the search – "dry EEG electrodes", "EEG electrodes", and others. If the results coincided, an earlier source was taken for review. The current review excludes studies focusing on the usability of electrodes and energy consumption, these points are discussed in detail in the following articles [78, 79]. Also, we will not dwell on this theoretical moment, because Doerrfuss, J., et al. [5], Neumann, T., et al. [6], Lin, B., et al. [7], Gargiulo, G., et al. [8] described in detail the theory of using dry EEG electrodes and a description of the physical process of measuring potential. We not considered wet electrodes because since they are different in structure with dry electrodes and in last

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and there are many works on this topic [80, 81]. Dry electrodes have several advantages and Fiedler, P., et al. [42], Kam, J., et al. [43] in their research described in detail the advantages of dry electrodes over wet electrodes. Kam, J., et al. [13] presented a comparison between dry and wet EEG. The authors showed that the performance was similar between dry and wet EEG sensors in the EEG amplitude, topography, and spectral power at rest. Dry/wet EEG electrodes might differ in other ways, for example, the standard (ANSI / AAMI), galvanostat and potentiostat, the effects of the radiation, the polarization. Since this remark is relevant to almost every work on the investigation of dry detectors, we will not mention this later every time in the analysis of the article and wrote general guidelines at the end of the manuscript.

For a clear understanding, we presented the structure of our review in fig.1.

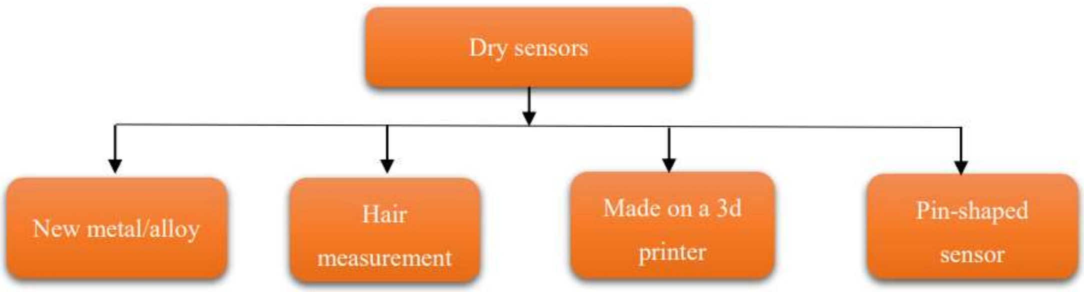


Fig. 1. Structure of review presented in the paper: new metal alloy - where new metals or their alloys were used in production, hair measurement - measurement of the EEG signal through the hair, made on a 3d printer - electrodes made on a 3D printer, pin-shaped sensor - electrodes of a special shape

## 2. Overview Dry EEG electrodes

### 2.1. Overview of manufacturers

Various companies are involved in the development of electrodes for EEG. We analyzed products from the following sensor manufacturers: Cardioline (http://cardioline.com/), Fukuda Denshi (https://fukuda.com/), Edan Instruments Inc (http: // www. edan.com.cn/html/enindex.html), Biocare (https://biocare.net/), Bionet (https://www.bionetus.com/), Enobio (https://www.neuroelectrics.com /). Manufacturers that mentioned above only produce simple/basic electrodes. . To evaluate the functionality of these sensors, we introduced the following studies where authors mentioned that didn't have any conflicts of interest. Mullen et al, [35] and Mullen, T., et al. [9] presented the papers where described EEG signal in real-time and its 3D visualization with dry electrodes from Cognionics (www.cognionics.net). Qian, C., et al. [10] proposed a combined label model, including the subjective part and the objective part, to reflect the influence of the affective state in real-time. The article briefly describes the test process and focuses on the conclusions drawn in the work. Yu, M., et al. [11] and Pei, G., et al. [12] presented for registration of EEG developed Brain Power system. But in these works, only general characteristics of sensors are given, and experimental studies are not sufficiently presented.

**2.2. Overview of new methods, ideas for the development and application of dry electrodes**

A few works with standard silver/silver chloride (Ag / AgCl) electrodes try to develop a new form of the electrode to improve the measurement [59, 60], but the papers did not provide convincing evidence of the advantages of new form electrodes. Silver/silver chloride EEG electrodes are the most popular and their characteristics as impedance are well studied. Typically, this electrode is used in conjunction with a brain-computer interface, Yohanandan et al. [63], Abiri et al. [64], and Lazarou et al. [65].

Flumeri, G., et al. compared wet electrodes with three types of dry electrodes (i.e., gold-plated single pin, several pins and solid gel electrodes). Authors showed that results with dry electrodes are comparable to those with wet electrodes in terms of signal spectrum and classification of mental states. Yeon, C., et al. [15] developed a non-invasive flexible multichannel dry EEG system. This innovative mounting of the sensor using the piston-cylinder-spring assembly for attachment to the scalp. Their study focused on attaching the electrode to the scalp.

The design of active dry electrodes for BCI systems based on EEG was presented by Lee, S., et al. [16]. The electrodes consist of easy installation and high EEG quality. In this work, only special sensors are used Zhou, X., et al. presented [17] a dry electrode which low noise. The prototype of the sensor, made in a 0.18 μm CMOS matrix, shows an input impedance of up to 18 Gm at constant current and 6.7 Gm at 50 Hz, as well as noise at the input current of 3.03 μA / VHz and total input noise (IRN) 0.67 μV rms in the frequency band 0.5–100 Hz. The reported characteristics of the sensor are among the best in this field. An interesting way to create an EEG electrode is to use a patterned vertical carbon nanotube (pvCNT) [18]. Electrode made on the round discs (φ = 10 mm) made of stainless steel. A long-term study shows minimal impedance impairment within 2 days [61]. These works [16, 17, 18, 61] are extremely difficult to reproduce as they have an individual character.

**2.3. Overview research with new alloys and materials for dry electrodes**

The physics of the process of creating electrodes by combining various alloys is described by Yu, Y. et al. [69] A few works study the possibility of using other alloys to create a dry EEG electrode besides the Ag/AgCl. [82, 83]. Camacho-Galeano E., et al. [19] analyzed in detail the characteristics of seven different materials (tin, silver, sintered Ag / AgCl, disposable Ag / AgCl, gold, platinum, and stainless steel) to produce the dry EEG electrodes. He showed that which is preferable to use gold, because line using gold electrodes does not create bias potentials. Fiedler, P., et al. [20] described a type of dry Ti / TiN electrodes. The result is that in the NaCl solution, the impedance of the Ti/TiN electrodes are from 824 to 54 Ohms, and the phase values are from 52° to 10° at frequencies from 5 Hz to 10 kHz, which approximates the values of the Ag / AgCl electrodes. Mota, A ., et al. [21] presented the development of a dry electrode for recording EEG by platinum. Tests showed that the prototype of the new electrode was able to measure EEG signals better than signals of Ag/AgCl electrodes. Liu, J., et al. [22] used a nano porous layer of platinum (Pt) that was deposited on the head of a dry electrode, reducing the contact resistance, and increasing the conductivity. The correlations between amplitude

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and latency the P300 (component of event-related potential (ERP) that manifests itself in the decision-making process) components obtained with dry and wet sensors were greater than 0.99. Similar methods were used by Kappel, S., et al. [23], where an electrode based on a titanium (Ti) substrate coated with iridium oxide (IrO2). To sum up, the dry electrodes measurements are comparable to wet electrodes in P300 measurement. Eventually, the disadvantage of these manuscripts is the lack of lengthy tests of the developed electrodes. As a rule, research authors are limited to short tests of various types of electrodes, after which they are compared. One of the main drawbacks in the development of electrodes with new metals is the lack of polarization effect, which directly affects the potential at the electrode. Agrebi, F., et al. [24] and Yang, C. et al. [25] disclosed in detail the polarization effect.

**2.4. Overview research involving the pin-shaped dry electrodes**

A Pin-shaped electrode is the most popular form of dry electrodes. The shape is necessary for the electrodes to pass through the hair to the scalp. Because there is no fixed rule of the number of pins on the electrode and electrode, the size, the exact design of dry EEG electrodes differs between studies. Yun-Hsuan, C. et al. [26] compared and received similar result for popular forms of dry electrodes, Fig.2.

Fig.2. Pin-shaped dry sensors in various designs

Kun-Peng, G., et al. [27] developed the pin-shaped electrode with bristles for measuring the EEG signal. The pins on the dry electrode were made of carbon fibers to reduce impedance. The tips of the pins were carbon fiber bristles which could better fit the scalp. Research showed that this type of electrode is slightly inferior in signal-to-noise ratio to wet electrodes. Koctúrová, M. et al. [28], did an assessment of two types of dry EEG electrode. One was a Ag/AgCl electrode, and the other was an electrode made of a flexible conductive polymer. Results showed that using a dry electrode with a higher resistance does not affect the measurement of the brain signal. Nathan, V., et al. [29] researched the effect of the number of pins on noise reduction. But they considered only one alloy and only one type of electrode. As a result, it is rather difficult to determine the relationship between the number of pins of pin-shaped dry sensors and the quality of the signal. Karacaoğlan, E., et al. [30] developed a silver active dry pin electrode for EEG measurements. The paper presents tests with reference to wet Ag/AgCl electrodes, which have shown the same results. One of the generally recognized disadvantages of this type of electrode is that the pins on them very often break. This results in an impedance mismatch making the results obtained during this time interval unusable.

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**2.5. 3D printed dry electrodes**

Given the growing popularity of using 3D printers in various fields, researchers have tried to use 3D printing in EEG studies. Krachunov, S. et al. [31], presented a study with 3D printed dry electrodes of various shapes (fig.3). The prototypes were compared with standard wet electrodes.

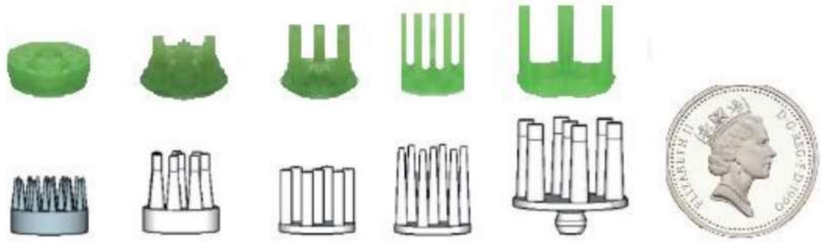
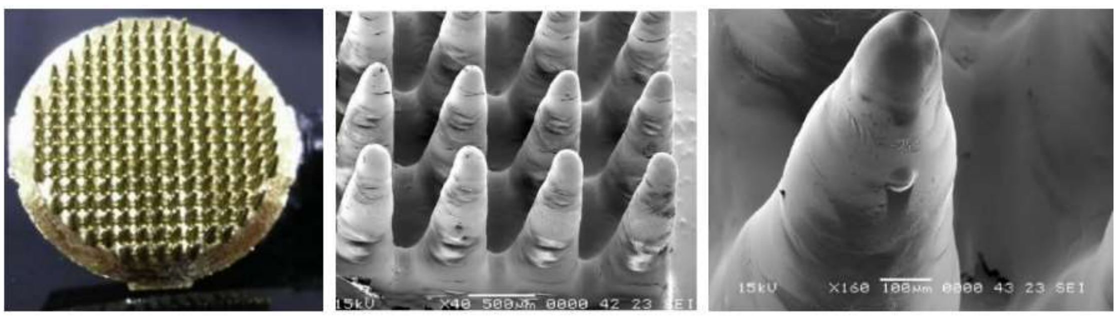


Fig. 3. Different forms for a dry electrode with a coin in denomination of one-pound sterling

Vanfleteren, J., et al. [32], described a protocol for manufacturing a dry electrode with a 3D printer. In the work, the electrode is made of an insulating acrylic-based photopolymer. It consists of 180 conical needles on a truncated conical base (fig. 4)



a b c

Fig.4. 3D printed dry electrode: a- common view, b - Partial SEM (Scanning electron microscope) image of c - SEM image of a 3D printed needle tilted by 45◦

The work also describes a metallization process consisting of two stages: sputtering of titanium as an adhesion-promoting layer and evaporation of gold to reduce impedance and prevent electrode oxidation. A comparison with wet Ag / AgCl electrodes for recording ECG-EEG showed similar results on the quality of the signal (SNR).

Research on the use of a 3D printer is a promising direction in the manufacture of electrodes because it allows you to create the shape of the electrode, depending on the need. But the processes of titanium deposition and gold evaporation are expensive therefore it is still necessary to consider ways to reduce their cost. At the same time, there is the same problem as for electrodes made on new alloys, namely the lack of lengthy testing and investigation of the magnitude of pro-polarization.

**2.6. Overview research in which dry electrodes measure EEG in hair**

There is a limited amount of research using dry EEG through the hair (i.e., no direct contact of sensor

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and scalp). But despite this Harland et al.[33, and Oehler et al. [34] describe this direction as promising. Mullen, R. et al. [35] presented an open-source software environment for online neuroimaging and state classification and the developed EEG system with the ability to measure potential through the hair. Modeling of work yielded high accuracy (AUC = 0.97 ± 0.021) for real-time assessment of cortical connectivity. Su, L. et al. [36] developed electrodes for EEG recording in hair. Alpha rhythm and stationery visually evoked potential were tested to verify the electrode. The result suggests that the accuracy of measurement through the hair has some magnetic fields noise.

### 3. Overview of non-contact sensors

In recent years, studies using non-contact EEG is increasing, which is especially noticeable in review articles [66, 67, 68]. This is driven by the need to make the measurement process more comfortable for patients. Sullivan, T., et al. [37] developed a noise-reducing proximity EEG sensor. The sensor comes with an electronic board for amplifying and converting an analog signal to a digital signal. The electrode is in the form of a metal plate in the lower part of the printed circuit board (PCB), which is covered with a mask for soldering the noise insulation of the sensor, fig.5.

a b

Fig.5. a - two-board structure of the non-contact sensor by Sullivan et al. [37], b - The bottom side of sensor. The metal plate on the bottom is the sensor, which is covered by a solder mask

Gonzalez, S. et al. [38] proposed a new non-contact EEG sensor design. The sensor lies between the variable inter-ring distance concentric ring electrode, and a segment annular coplanar capacitive tilt sensor. This non-contact electrode improved the accuracy of the Laplacian estimation, increasing the communication ratio of the EEG, and improving artifact attenuation [fig.6].

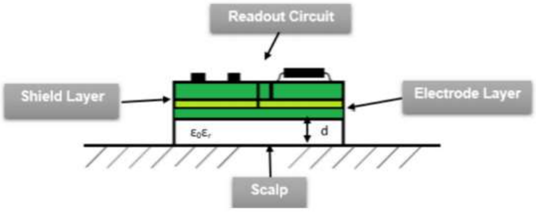


Fig. 6. PCB capacitive electrode cross section

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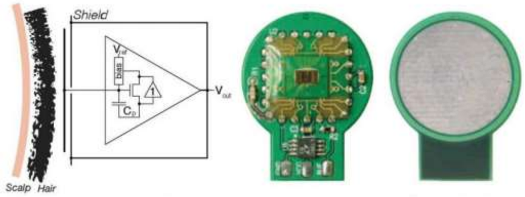
For the most part, the content of this work consists of a description of the technical development of the sensor. This work is more hypothetical which needs more empirical evidence to verify the effectiveness of the design. As well as Yu, M., et al. [39] who presented small non-contact EEG sensors for portable EEGs, Fig. 7.




a b c

Fig.7. a - integrated non-contact electrode concept, b - bottom sensing plate view from above, c -bottom sensing plate

Data from a contactless electrode showed a maximum Information Transfer Rate ITR value of more than 19 bits/min with 100% accuracy, versus 29.2 bits/min for wet electrodes and 34.4 bits/min for dry electrodes, which is a good indicator for contactless sensors. Yu, M., et al. [40] presented wireless and contactless EEG electrodes. Each electrode provides a gain of 46 dB in the frequency range of 0.7-100 Hz with a noise level of 3.80 μV to ensure the high quality of the recorded electrophysiological signals. A common disadvantage of using contactless sensors is that the amplitude levels are so low that they cannot capture short-time EEG signals. At the same time, there is high impedance with the non-contact electrodes, therefore it is necessary to use an amplifier with ultra-high impedance in the electronic circuit. Nevertheless, the above-reviewed studies still show the feasibility of using non-contact sensors in the future even they are now seemingly inferior to the contact EEG.

## 4. Conclusions and discussion

In this paper, we presented an overview of dry and non-contact EEG electrodes. We reviewed multiple works evaluating the effectiveness of their developed dry or non-contact EEG devices. To compensate for the absence of standards to judge the effectiveness of the EEG device, we recommend the following to be considered when developing and testing dry electrodes.

**When developing dry electrodes:**

- Need to use the electrochemical interface, such as Solartron 1287A. Using a galvanostat, we can maintain a constant current in a specific cell, regardless of the potential difference of the electrode. Using the potentiost, which is an electronic device, it is we can automatically control the potential of the electrode and maintain the set voltage value on this electrode;
- It is necessary to measure the internal noise of the electrode;

- Before research, it is necessary to verify that the cable of electrode has immunity to frequency in the power line, immunity to radiation of radio frequencies, and immunity to radiated radio frequencies. The reduction is possible with the help of silver, graphite, and unshielded versions of screens.

**When testing the developed EEG:**

- Generally accepted that wet electrodes are a recognized standard, in works in which the development of a dry electrode appears, it is necessary to make a comparison with wet electrodes. In this case, it is necessary to use the standard (ANSI / AAMI) EC-12: 2000 standard for disposable electrodes. https://webstore.ansi.org/standards/aami/ansiaamiec122000r2015;
- It is necessary to use laboratory analyzers of impedance and amplitude-phase characteristics. For example, Solartron 1260 with a nominal accuracy of 0.1% from 5 ohms to 100 kOhms. In previously reviewed manuscripts represented impedance, but there is no information on how it was measured;
- The presence of artifacts, the analysis of the obtained EEG is expediently carried out in conjunction with a neurophysiologist;
- Before testing, it is necessary to provide information about the patient's skin, resistance, and impedance;
- Only a few of the reviewed manuscript used data collection and analysis using the CorrWare software (http://www.scribner.com/software/), CorrView, ZPlot and ZView (Scribner Associates Inc. Southern Pines, NC, USA). It is advisable to use more than 1 software to ensure a more reliable result;
- Present graphs with noise voltage level. It was done in only a few works [17, 23];
- Need to refer to the standard of medical equipment (EN 60601-1-2), which describes tests for resistance to the power line frequency (50 Hz), magnetic field test (EN 61000-4-8), and resistance to Radio Frequency Test (RF) emissions (EN 61000-4-3). https://www.psma.com/sites/default/files/uploads/tech-forums-safety-compliance/resources/iec60601124thedwebinarna-2.pdf https://standards.globalspec.com/std/1248855/EN%2061000-4-8 https://www.emcstandards.co.uk/files/61000-4-3_immunity_to_radiated_rfi.pdf

We didn't find any research which fully meets the above requirements. As close as possible to a full assessment of the electrode is the thesis [41], but it is devoted to the development of a wet EEG electrode. The author recommends the necessary tests for a comprehensive check of the dry electrode. We hope this would provide a guideline for the development and performance assessment of the dry or non-contact EEG in the future.

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**Ethical Approval**: Not required

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