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Biosignal Quality Control in Real-World Intelligent Environments

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Abstract. Despite the wealthy of information biosignals cary, with Intelligent Environments (IE) they are often disregarded. We discuss issues we faced with integrating reliable biosignals into a real-world IE. These include the limited conductivity of dry sensors, movement artifacts, and placement issues. Subsequently, we introduce a real-time Signal Quality Indicator (SQI) for ElectroCardioGram (ECG), which consists of a Signal Loss Indicator (SLI) that detects signal capping, flatlining, high-frequency noise, and low-frequency noise. If the SLI detects a signal, the Signal Usability Indicator (SUI) subsequently processes the signal using the reference Pan-Tompkins algorithm and a dedicated filter to extract heart rate. The SQI marks what parts of the signal can and cannot be used for analysis. As such, it allows empirical calibration and, hence, the use of biosensors in real-world IE.

Keywords. intelligent environments, signal quality, reliability, sensors, biosignals

1. Introduction

In the development of Intelligent Environments (IE) , numerous challenges arise from both the engineering and human aspects [1,2]. Effective communication between these two dimensions is crucial for the success of an IE project. The intelligence of an IE relies on high-quality signals as input; without them, achieving intelligence is impossible. This was evident in our IM-TWIN IE project[2]. To ensure optimal performance, we had to gather and fuse data streams from various sources, such as cameras, microphones, intelligent stuffed animals [3], and sensorized clothing, all in real-time [1].

During the current stage of IE development, big data and deep learning are not the ultimate solutions due to the lack of "big" data, rendering deep learning infeasible [1]. IE systems must be personalized and calibrated to individual users, who can vary significantly from one another [4]. Despite utilizing the same design principles, network controllers, communication protocols, and sensors, the parameters of personalized IE systems will differ. Personalized IE can consist of the same building blocks; but, their parameters differ significantly, as we all experience our own every days.

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Starting from the principle that the further one goes back in the processing chain, the larger the impact one might have, we examined the signals we obtained. Each having their own challenges. We studied biosignals, which showed to be the hardest to process. In particular, we examined one, deemed to be the most challenging and most promising: the ElectroCardioGram (ECG) (also known as EKG), which is claimed to be the most informative one both with respect to physical and mental well-being [5].

The incorporation of biosignals in IE is seldom explored [6,7,8,9], likely because they originate from users rather than the environment. However, integrating on-body biosensors into IE systems is advantageous, as these signals complement conventional sensors such as cameras, microphones, and location tracking. Studies have shown that machines can outperform humans in emotion detection when biosignals supplement data streams from cameras and microphones [10,11]. Furthermore, unlike with conventional sensors, users cannot easily conceal their state using biosignals. Additionally, biosignals do not suffer from traditional disadvantages, such as occlusion, that affect other sensors [1,12,13]. Examples of IE that could benefit from ECG include smart healthcare facilities, assisted living homes, stress management, and fitness monitoring systems.

In the following sections, we discuss the complexities of incorporating biosignals into IE. Section 3 delves into a Signal Quality Indicator (SQI) that enhances the reliability of signal acquisition during IE development. Finally, Section 4 provides a concise conclusion.

2. Assessment of ElectroCardioGram (ECG) Signals

Physical activity is reflected in our biosignals. To reduce our body temperature, our sweat glands become more active when we run. Simultaneously, our Heart Rate (HR) increases as we need more oxygen. However, our biosignals reflect more, much more. Biosignals can also unveil both our state of physical and mental well-being. To determine what is reflected on what moment is complex, yet potentially very informative. In particular in IE, where multiple signals are captured in parallel and context information is taken into account, biosignals can flourish.

We investigated the performance of the ECG signal. ECG is the most used biosignal and its signal quality can be conveniently compared due to its low latency and continuous character. At the same time, ECG is one of the hardest signals to obtain, seen from a physiological standpoint. Where most biosignals are obtained using only one or two electrodes (e.g., ElectroDermal Activity (EDA), and ElectroMyoGraphy (EMG)), ECG requires at least three electrodes [5]. The extra electrode acts as a reference or ground.

Extracting high-quality biosignals is one of the main challenges of the ERC-funded Horizon 2020 IM-TWIN EIC Pathfinder project. Unfortunately, the situation is complicated even further as we cannot use the well-known, golden standard gelled (also known as: wet) electrodes. Wet electrodes are avoided as they can only be used once and require a tedious attachment process. Dry electrodes, which do not require gel, are preferred. Dry electrodes could be textile embedded; for example, embedded in a tight-fitted t-shirt. However, dry electrodes have several disadvantages [14,15].

Gel acts as a conductor between the skin and the electrode. Measuring the tiny electrophysiological signals without gel is hard. Dry electrodes tend to have more difficulty measuring high-quality biosignals as the cushion of air between the skin and the electrode acts as a giant transistor, masking the small biopotentials [14,15]. Figure 1 shows the difference between wet and dry electrodes in more detail. Mathematically R_i is often larger than R_g. Moreover, dry electrodes are not fixed to the skin. Hence, electrodes tend to shift during body movements, causing conductivity to vary with the local variations across the skin's surface.

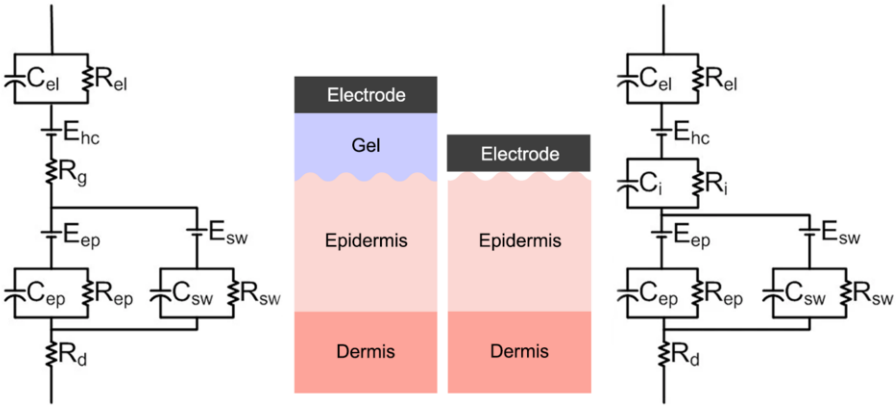

Figure 1. Electrode-skin interaction of wet and dry electrodes adapted from[16]. The corresponding electrical circuit representation of each situation is also shown.

In contrast to many other studies, we aimed to investigate the performance of an easy off-the-shelf implementation of dry textile-based electrodes. We deliberately did not use advanced techniques to embed dry electrodes into the fabric to explore the challenges of textile-based electrodes and set a baseline performance on which improvements could be made.

Using a biosignals PLUX professional kit[3], both dry and wet electrodes are used to compare performance. The biosignals PLUX professional kit records up to 8 signals simultaneously using a small, portable recording unit. In turn, the recording unit sends the data via Bluetooth to nearby computing machinery. As the recording unit operates wireless, users can move freely, and obtrusiveness is kept to a minimum.

The dry electrode setup was created by attaching three commercially available non-gelled Ag/AgCl electrodes to a tight-fitted Kipsta thermal shirt. This shirt was selected such that the shirt sat tight around the entire upper body. Three holes were punched in the thermal shirt for the positive (red), negative (black), and reference (white) electrode. Electrodes were placed in the V2 configuration of the 12-lead ECG scheme [5]. Reference was placed on the sternum due to the relatively short wiring (2-3 cm). Three electrode plates were attached to the electrodes such that the thermal shirt was clamped in between (see Figure 2a).

In the wet electrode setup, electrodes were pre-gelled and attached to the unshaven skin in the same V2 configuration as the dry electrode setup (see Figure 2b). The skin

[3]URL: https://www.pluxbiosignals.com/products/professional-kit [Last Accessed: 13 April 2023]

was not shaven or cleaned before attachment to stay as close to the dry electrode setup as possible. This way, only the usage of gel and adhesive electrodes was added to the setup.

During all experiments, the participant was seated on a chair and tried to move as little as possible to prevent motion artifacts. Each implementation was tested for a brief period, during which signal quality was visually assessed and noted down. With the dry electrodes, several variations were tested on the fly, which are reported in Section 2.1.

2.1. Experimental Results

Using the wet electrode setup, the reference ECG was recorded (see Figure 2b). As expected, the resulting signal was largely noise-free. The P, QRS, and T waves can be easily recognized, as shown in Figure 2b right side. The high-frequency noise imposed on the signal was the well-known 50/60 Hz powerline interference.

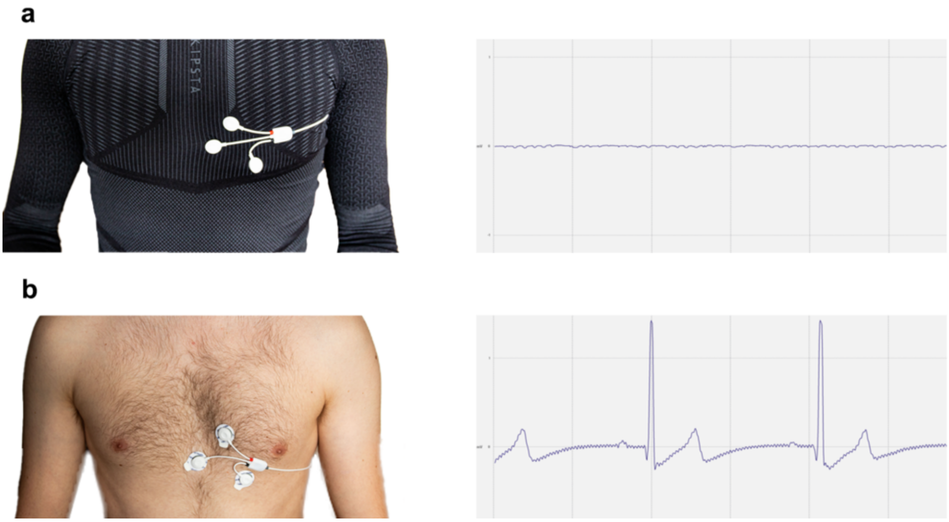

Figure 2. Setup and ECG signal resulting from the a) dry and b) wet, reference electrode implementation. In the wet electrode setup, gelled electrodes were attached to the skin, using an adhesive membrane. Electrodes were configured in the same V2 configuration as the dry electrodes.

Electrodes were not pressed against the skin besides the pressure generated by the thermal shirt. One can easily see that the signal is unusable. None of the ECG waves are present.

To improve the signal quality of the dry electrode implementation, the pressure on the electrodes was increased. Theoretically, the amount of surface contact of the electrodes on the skin would improve. Reducing the amount of air between the skin and the electrodes decreases R_i from Figure 1. Indeed, the ECG signal quality improved significantly, almost up to the level of the wet electrode ECG signal (see Figure 2). A difference was observed in the detection of the P-wave, which was absent in some cases. Further, while pressing, the reference electrode (white) was floating above the skin. The cavity created by the chest muscles prevents the reference electrode from touching the sternum.

The commercially available dry electrodes are delivered with a blue plastic stabilization ring to increase fixation area. However, when the electrode is pressed into the skin at an angle, the ring hinders surface contact. By removing the blue plastic stabilization rings, we tried to improve skin-electrode contact. Unfortunately, Figure 3 shows a different result. In contrast to the result with the stabilization ring, we got a signal that largely consists of a high-frequent, large-amplitude noise component. The standard ECG waves are unrecognizable. However, there are hints of periodicity.

Based on the additional pressure experiment findings, we hypothesized that the signal could have been heavily distorted because the reference electrode was floating above the sternum. Therefore, instead of pressing the electrode on the sternum, we tried another ground electrode placement by simply holding the reference electrode between the right hands thumb and index finger.

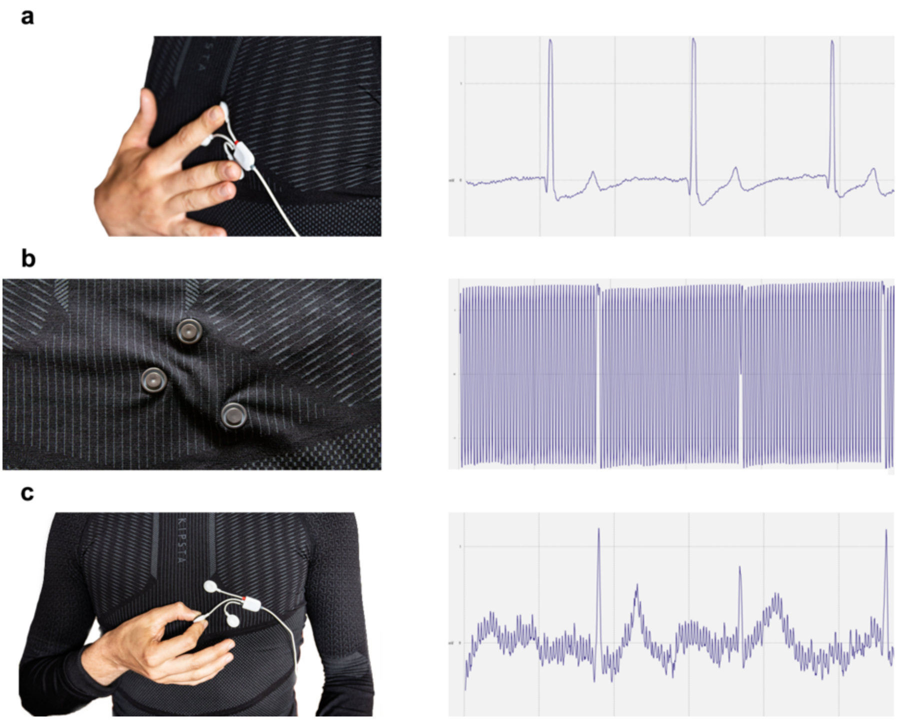

Figure 3. Three strategies to improve signal quality of the dry electrode implementation: a) Pressing on the dry electrodes, b) removing the blue stabilization rings for better skin contact, and c) holding the ground electrode. When pressing on the electrodes, the QRS and T waves can be recognized easily. The signal remains unusable when the plastic rings are removed. When fixating the ground electrode, the signal shows workable.

ECG signal quality can be improved significantly if the reference electrode can do its job adequately. Although signal quality is lower when compared to the wet electrode setup or when applying additional pressure, it still provides a usable signal. The high-frequency powerline interference could be filtered. From the resulting ECG signal, R-peaks and even T-waves could be detected.

The experiment showed that the sternum electrode hovered a few centimeters above the skin because of the cavity that was created by the muscles in the chest. No matter how tight the shirt, these sorts of cavities are unavoidable. Therefore, avoiding these places at all is the only solution for maintaining good skin-electrode contact. As such, a different lead configuration should be adopted. Following the Einthoven principle [5], one should measure Lead I (i.e., horizontally across the body) to obtain a decent estimation of the QRS vectors magnitude. Further, as we are primarily interested in QRS complex detection, electrodes do not have to be close to the heart. Atrial depolarization causes an electrical field large enough to be measured across multiple places across the torso. Therefore, further research regarding alternative electrode positions could be interesting.

3. Signal Quality Indicator (SQI)

The acquisition of good quality biosignals is valuable for IE as in the IM-TWIN project. Without proper data streams, applicability is limited. Unfortunately, physiological data streams acquired with the use of dry non-adhesive electrodes are vulnerable to numerous sources of noise that are not fully avoidable. Consequently, the aim should not be the complete removal of noise, but instead to reduce it to an acceptable level; thus, elevating the Signal-to-Noise Ratio (SNR) above a predefined quality threshold. To facilitate the development of algorithms for this purpose, we have developed a SQI to assess both the quality and usability of the signals.

Signal quality is a vague concept. It is evaluated both qualitatively and quantitatively [5]. Qualitative analysis typically involves observing the signal, which is subjective and tedious for longer signals. To this end, we sought to evaluate the quality quantitatively and automatically, allowing a real-time, unbiased, controlled analysis of the signal. To achieve this goal, we have designed two systems that together form the SQI : a Signal Loss Indicator (SLI) and Signal Usability Indicator (SUI) . When developing IE , both are important.

3.1. Signal Loss Indicator (SLI)

Body movements and other actions stress the skin-electrode contact by inducing shearing forces upon the electrode. If an electrode loses contact with the skin, no signal can be recorded anymore as the air between the electrode and the skin will act as a massive insulator preventing any electrophysiological signal from reaching the electrode. Consequently, signal loss is experienced as seen in the previous section. Unfortunately, it is not trivial to detect signal loss. Losing skin-electrode contact causes chaotic behavior which is difficult to distinguish reliably from noisy but usable ECG. We tackle this issue by identifying four types of signal loss (see Figure 4).

For each of these types of signal loss, a dedicated indicator algorithm was developed based on [17]. In the end, the masks these four indicators are merged resulting in a final signal loss mask.

3.2. Signal Usability Indicator (SUI)

An SLI approved signal could still be contaminated with motion artifacts. The SLI solely checks if there is no information lost. It does not check whether or not this information is buried under noise. Therefore, we developed the SUI , which checks whether or not heart rate analysis is feasible.

Using the reference Pan-Tompkins algorithm [18], SUI detects heartbeats detection on the remaining segments of data after signal loss removal. The algorithm detects QRS

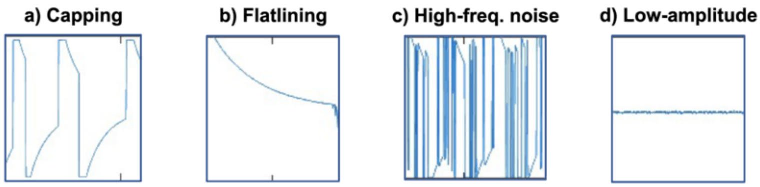

Figure 4. We identify four types of signal loss. a) Signal capping, when an analog signal reaches the digital boundaries and is automatically limited, losing the information above the limit. b) Flatlining, if, suddenly, a signal contains no information. c) High-frequency noise, when a signal has a very low SNR ratio. d) Low-amplitude noise, when a signal does flatline but still hovers around due to tiny background noise fluctuations that are not strong enough to cause a type 3 signal loss.

peaks in ECG data and is still among the most used ECG algorithms. Next, the Inter-Beat Interval (IBI) between two successive heartbeats are calculated. Missing a heartbeat causes an abnormally large IBI . Vice versa, detecting a false beat creates an unusually short IBI (see peaks in Figure 5).

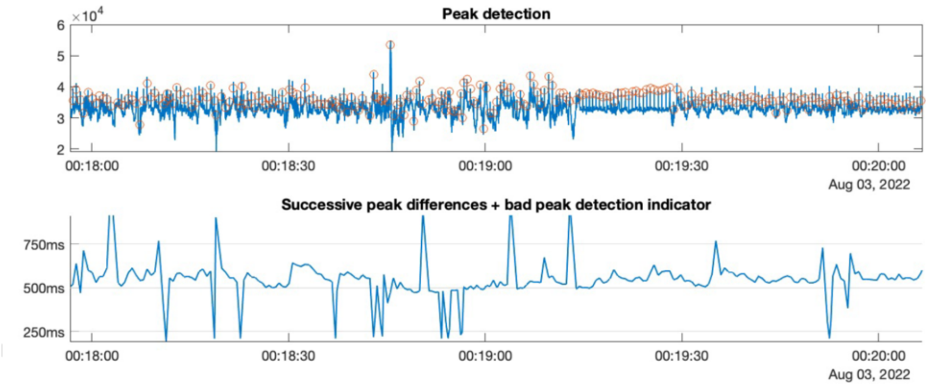

Figure 5. The two phases of usability assessment. First, ECG peak candidates are extracted from the incoming ECG signal using the Pan-Tompkins algorithm. The number of missing and falsely detected peaks is then assessed by calculating the successive peak differences. Missing a heartbeat causes an abnormally large difference. Vice versa, detecting a false beat creates an unusually short difference.

As a quantitative metric for signal usability, we use the number of misclassified beats. Missing many beats or detecting many false beats makes it increasingly difficult to perform proper Heart Rate Variability (HRV) analysis. However, short peaks (i.e., misclassifying only one beat) are not a problem if scattered throughout the signal. Hence, we filter out short peaks by subtracting a median filtered signal from the original signal:

$$residue[t] = IBI[t] - median(IBI[t-2], \ldots, IBI[t+2]) \quad (1)$$

$$usable[t] = \left\{ \begin{array}{ll} \texttt{yes}, \text{ if } \sum_{i=-7}^{7} residue[t+i] < 1.5s & \\ \texttt{no}, & \text{otherwise} \end{array} \right\}, \quad (2)$$

where we take the residues sum over 15s windows, which allows using a 1.5 seconds threshold to classify 15s windows as either usable or unusable. The result is a binary mask that is merged with the binary signal loss mask to obtain the final signal quality indicator mask.

$$SQI = (\neg SLI) \cup SUI \tag{3}$$

3.3. SQI Results

We evaluated several data samples with the SQI . The summary of one of these assessments is plotted in Figure 6. The masks of all five quality indicators: the four SLI s and the SUI) are merged into a binary good and bad signal mask represented as green and red regions, respectively. A good signal provides good input for HR and HRV analysis. In contrast, HR and HRV measures obtained from Red regions are unpredictable and unusable for analysis.

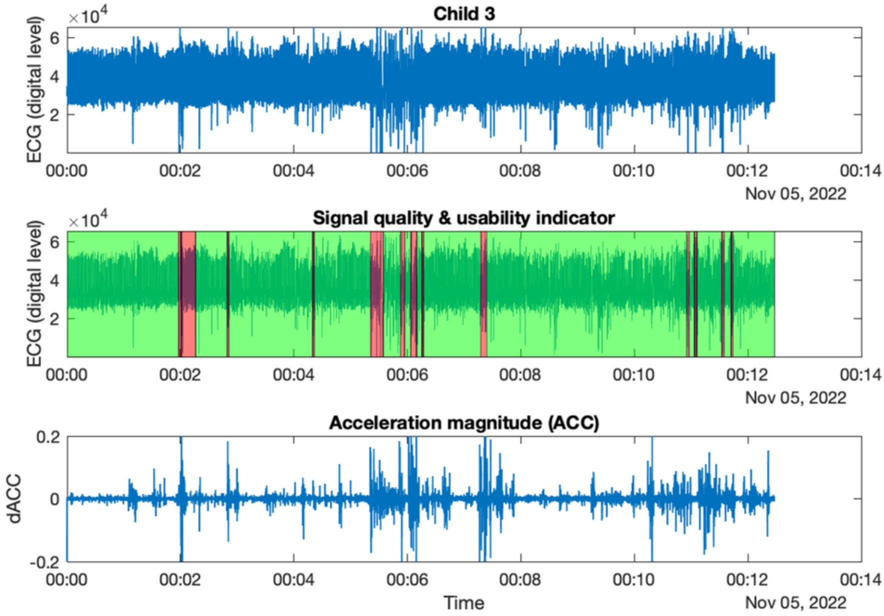

Figure 6. Signal quality assessment results on pilot data from one subject together with the magnitude of acceleration. The signal quality indicator outputs one binary output signal that highlights good and bad signal segments as green and red shaded regions. The quality correlates with body movement as we are using dry electrodes that tend to shift during movements.

As shown in Figure 6, body movements negatively affect signal quality. Although efforts have been made to remove this effect, it's not possible to get rid of it completely. However, we can lessen the impact of body movements by improving the fit of the t-shirt. A well-fitting t-shirt helps to reduce the negative effect on signal quality. To tackle this issue, we created a real-time SQI that can assist in the development of IE . Figure 7 demonstrates its use with Electrocardiogram (ECG) biosignals in one experimental setup; a young child moving around freely. Future studies could explore the SQI in different settings to gain a broader understanding. Ideally, the SQI is used together with an IE development process to make the most of sensor technology, such as wearables.

Figure 7. The real-time SQI provides easy-to-interpret feedback about signal quality. When used in combination with properly defined startup protocols, signal quality can be assured in every measurement session.

4. Conclusion

The development of IE is one of numerous challenges [1,2]. One of these challenges involves ensuring high-quality signals that permit conventional analysis. This is particularly crucial in many IE applications where large-scale data generation is limited, thus hindering the use of deep learning techniques.

The SQI offers a dependable and objective method for evaluating biosignal quality and could easily be extended to other signal types. By detecting absent and erroneous heartbeats, the SQI categorizes four types of signal loss and appraises signal usability. By consolidating this information, the SQI generates a binary output signal that distinguishes between 'good' and 'bad' signal segments.

The real-time SQI delivers instantaneous feedback on one-dimensional data streams. As such, it serves as a valuable tool for IE developers striving to produce intelligence with small data sets.

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