Study of Noise in EDA signals

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Abstract - EDA signals detects changes in electrical conductance of skin and is thus closely associated with our nervous system. There are a lot number of things that can affect an EDA signal ranging from humidity in air to sympathetic arousal and that gives room for noise. Most of the work in noise removal in EDA signals have been based on templates, which are good for a particular task but most of the time result in smoothing out the non-noise part of the data too. In this project, we have tried to study noises and see if we can come up with a pattern which a particular type of noise follows and if can remove it without touching other parts of data.

1. Introduction

EDA stands for Electro Dermal Activity and in broad term used to study the electrical properties of our skin. Electrical conductance of skin is the most widely studied wherein we apply a potential difference between two points of skin and study the electrical current flow between them. EDA signals are closely associated with sympathetic arousal in a person. An EDA includes both background tonic (skin conductance level: SCL) and rapid phasic components (Skin Conductance Responses: SCRs) that result from sympathetic neuronal activity. Since, it's been closely associated with sympathetic neuronal activity, it has become a hot topic in human psychology.

The reason behind EDA being associated with our nervous system is straightforward. Sweating is controlled by sympathetic nervous system [1] and the electrical resistance of skin varies alot depending on the state of sweat glands in skin and EDA signal is used to study the electrical properties of skin. The skin conductance increases as the sweat glands activity increases. If the sympathetic nervous system is highly aroused, then sweat gland

activity increases, which in turn increases skin conductance. In this way, skin conductance can be a measure of emotional and sympathetic responses.
Noise in EDA signals can be induced by a lot of factors. As more and more research is going on in this field, we are having the subjects wear the EDA devices and go about their day to day work. This has bound to have noise. Even when a subject is sitting in a room and someone slams the door while leaving the room, it will create some noise because the subject is startled. Noises can be of two types: External and Internal. External noises are the noises which are induced by the environment in which the subject is being tested. It can be humidity, high temperature, slamming of a door etc. Internal noises are a bit hard to study. It is related to things inside the human body. Things like blood pressure, heart beats etc. creates noises.

2. Related Work

1. Effect of Movements on the Electrodermal Response after a Startle Event[2]

The EDA signal reacts quickly to an external stimuli, such as startle events. This kind of arousal is called “fight or flight” reflex, an unconscious reaction to an unexpected frightening event. The startle event leads to a peak-shaped response in the phasic part of the signal.

During each session of the experiment, the subject was listening to classical music containing ten random bursts as a startle event. For the movement part, they had their subjects run on treadmill for different speeds - 1 km/h, 3 km/h and 6 km/h. For better results, they asked them not to use the handle of the tread and try to walk or run naturally. The sensors were placed on the fingertips and the “Emotion Band”, which contains the circuitry, was placed on the arm. A total of 5 subjects were used in the process.

According to their findings, the faster a person is walking the more the peak distribution of the EDA is approaching a uniform distribution. However, even at a walking speed of 6 km/h the effect of the startle event is statistically still visible in the EDA.

2. Automatic Identification of artifacts in EDA[3]

In this experiment, the aim was to give out a semi-supervised machine learning technique to label and remove noise. The idea was to ease the process of collecting EDA on large scale which is being proposed these days.

The data used in this analysis were collected during a study in which 32 participants completed physical, cognitive and emotional tasks while wearing Affectiva Q EDA sensors on both wrists. The Q sensor collects EDA data by measuring skin conductance (SC) in microSiemens (μS) at a frequency of 8Hz.

The code they developed is freely available on their website: eda-explorer.media.mit.edu

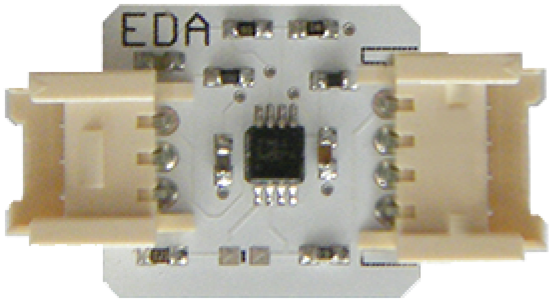
3. Experiment Description

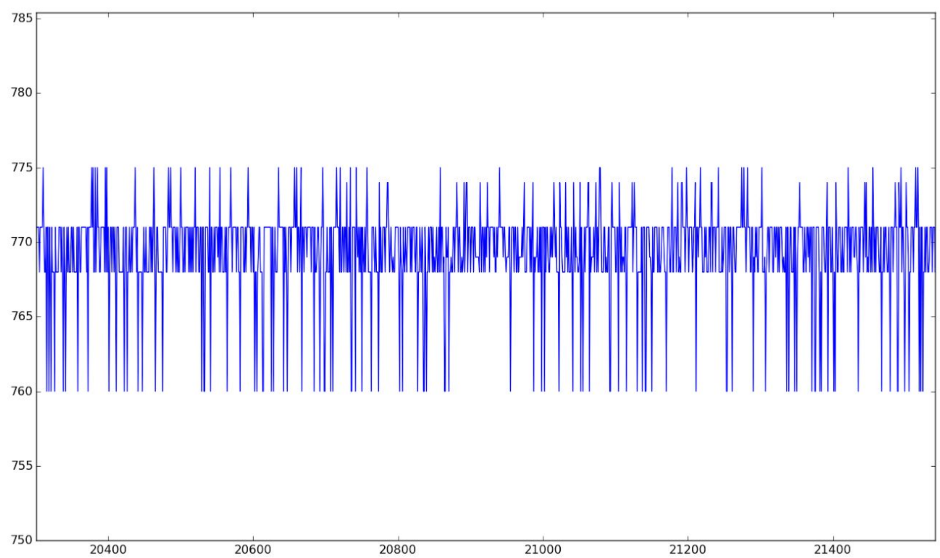
In our experiment, we have placed the EDA sensors on the tips of the fingers which is the most sensitive and most encouraged position to take EDA signals. The subjects were taken to a room and were allowed to make themselves comfortable for about 15 - 20 min. The EDA board is connected to the laptop via bluetooth and we are running OpenSignals software for this purpose. It's a free software available for Windows and Mac OSX.

At first, we collect the EDA signals for rest data. It forms the baseline. Until the baseline is stable, we don't move forward to collect any sort of data. It clearly means the subject is still not comfortable and probably needs more time to settle down. The subject is NOT informed of what is coming on their way as that would mean they are expecting it and it might create "meta-noise". They are also said to think something mechanical such as counting in their head or thinking about typing something, things which don't involve emotion since, emotion always affects EDA signals.

Once, the rest data is collected, one of the experimenters moves forward and pinches the subject. The movement should seem casual and it shouldn't startle the subject. It has been observed that this always raises the EDA signal a notch and after a while it goes back to normal.

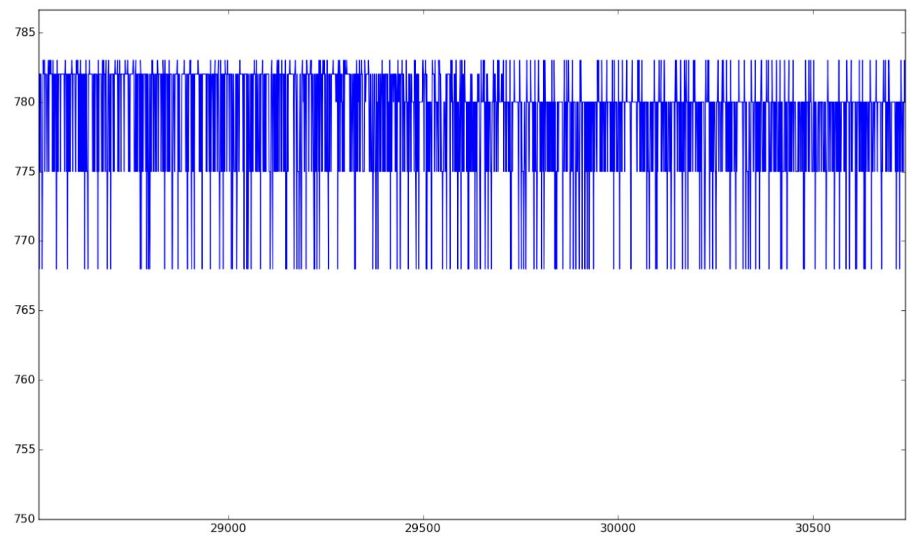
Firstly, we have visually tried to analyse the signals and find out what are possible features or models that we might look for. The signals had clear distinction in visuals. Though from visually seeing a data it is very hard to tell which is a noise and which is important signal but as you can see from signals below, there is a very clear distinction in the signal for rest and noise.





Rest Data Graph for One of the Subjects

As you will see in the below graph that the frequencies of the signals differ a lot. The graph during the noisy period has a lot higher frequency than that of the rest data. This clearly shows the electrical activity of the skin in that period is high.



Signal snippet when the subject is under external noise (pinch, in our case)

So after studying the 2 signals, we tried out different approaches to try and distinguish a noise from an important activity of the brain. So since there is quite some difference in frequency, we tried out methods like standard deviation of the signals from mean in a sliding window, zero crossings, slope detection in sliding window etc. Among them standard deviation give quite some distinctive results, however we are still not in a position to draw conclusions as we don't have enough data.

Tools/Softwares used: Numpy, matplotlib, EDA board, OpenSignals

5. Methodology and Algorithm

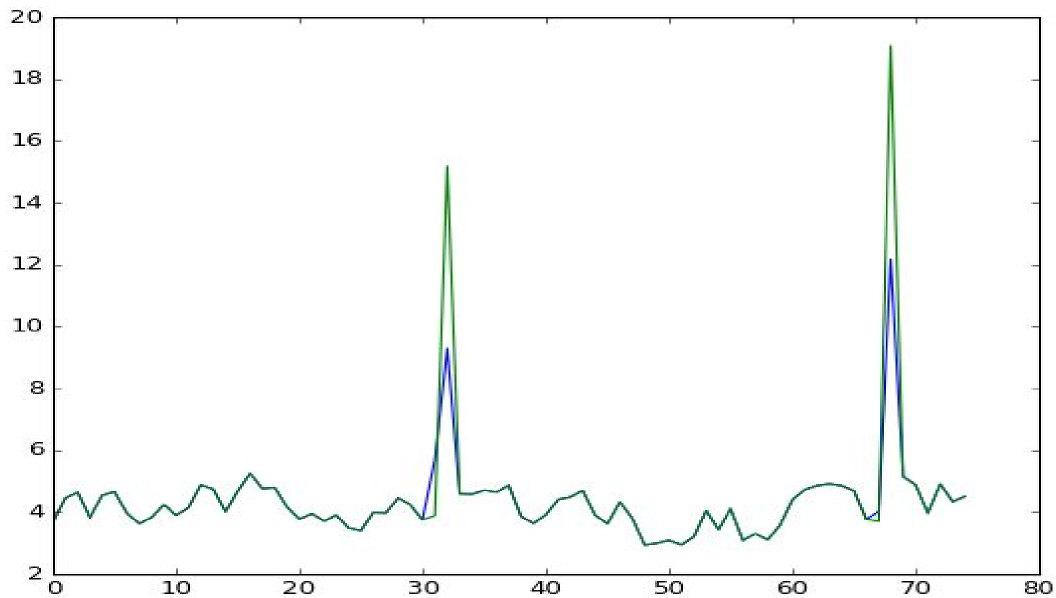
1. **Data pre-processing (mainly cleaning):** The matlab output we get after inputting the collected signal contains a bunch of things, not all are of our use. So, we wrote code to filter out the required data.
2. **Error Detection:** There are two types of errors which we will be talking about here.

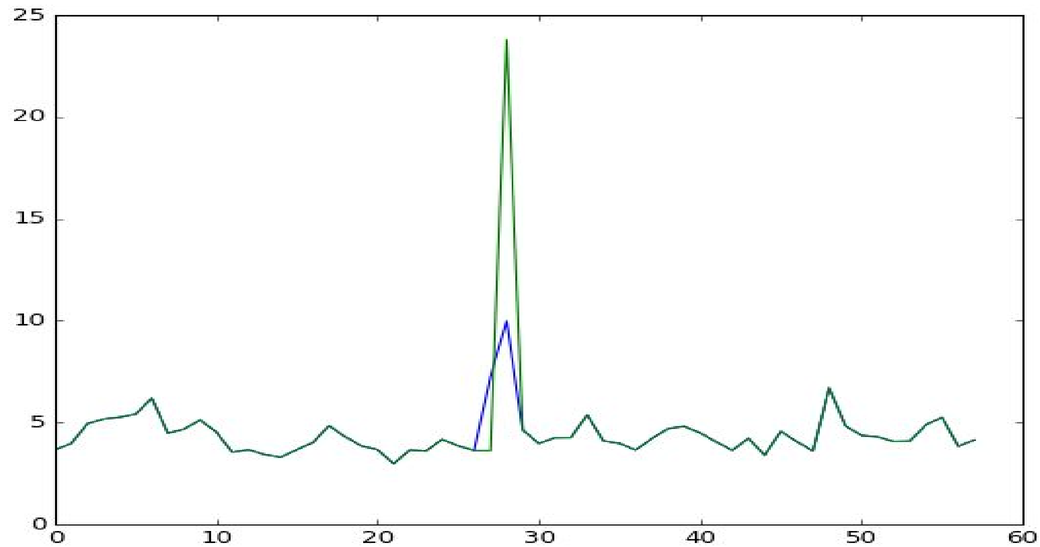
    A.. Device Error: These are the errors caused by the device. Sometimes during our collection of data, we got steep changes in signal without any presence of noise. Since, changes eda signals can be caused by one's thought, we confirmed whether the test case had some thought during that

time. After finding out that this was happening a bunch of time, we deduced that it's a problem from device as nothing else can affect the signal.
These types of errors were easy to detect. These are distinguished by steep changes. Also, two points that should be noted are: the frequency of value of standard deviation is generally high - if you just consider the integer value of the standard deviation and device errors don't happen *that* often. So, the first filter we applied to detect this device error was the frequency count on it. If the frequence of the *integer value* of the standard deviation is under some particular value (we took 5) that means something odd is happening there.
For the second filter, we take all the values from the first filter and put it in a list. Then, we parse the output data once more. This time we take a window of 1000 and check delta of zero crossings of all the values in the window, if it's greater than a fixed value(150 in our case), we confirm that we have got a device error at that point.

B. Artefact error : This error should be present because we are creating noise for this error to occur. For creating artefacts, we tried 2 different types of simulations - clap and pinch. To find the error, we first took a fixed window and incremented it over our data. We have data points for each millisecond. So, if we have data for 60 seconds, then there are 60, 000 data points. We moved the window over these data points and calculated the number of zero crossings and the standard deviation for data points in the window. We also tried calculating the average slope of the window.
But we found that the best detection was given by **standard deviation.** It helped us to narrow down to 2-3 seconds for the error. How we did this is we used a window of 5 second and found out the window in which the error occurs. Now to check whether this standard deviation is actually an error peak or a property, we calculated histogram and took the rightmost element (highest amplitude) and also least occurring. Then we checked whether this standard deviation has a delta of more than 5 with it's neighboring standard deviations. This helped us get the error time detected to 2 -3 seconds.
Then we run a sliding window over this 2-3 seconds to exactly find out which is the range of data that causes the steep rise in standard deviations. This helps us to narrow it down to the exact time range for which the effect remained. It varies from 0.4s to 1.6s in our data.

3.. **Error Correction:** For the device error, it is just a single datapoint. So, we replace the datapoint by the maximum occurring amplitude in that window. This removes the device error. For the artefacts the idea is since, we narrowed down the time of the noise in the detection part, we will replace the *noisy* part with values from the windows before and after the window where the noise occurs. This helps us remove the artefacts though there might be better ways. Here are the example plots to display the error detection and correction. The *high* values are the errors detected and the blue lines overlapping on them are the corrected values.





6. Results

The overall findings of the experiment is tabulated here. Note that the since we are dealing with brain data, the subject's name should not be disclosed. Hence, we have altered the name of the subjects.

Device Error Detected

Test Case	Device Error Detected/Corrected	Error Value	Replace Value
1	Yes	1016	760
2	Yes	1016	768

Artefact Detected

Sl. No	Error Correct	Annotated Time (Pinch)	Detected Time (Pinch)	Annotated Time (Clap)	Detected Time (Clap)
1	NO	35 - 38s	ND	16 - 19s	ND
2	NO	15 - 17s	ND	39 - 41s	ND

3	NO	40 - 44s	ND	14 - 17s	ND
4	NO	16-20s	ND	40-45s	39.8 - 40.6s
5	NO	36 - 41s	ND	22 - 26s	22.6 - 23.4s
6	NO	35 - 38s	ND	16 - 21s	17 - 18s
7	YES	8 - 12s	ND	17 - 19s	16.2 - 17.2s
8	YES	64 - 68s	67.4 - 68.6s	29 - 34s	31.2 - 32.2s
9	NO	42 - 45s	46.8 - 47.6s	24 - 28s	29.8 - 30.4s
10	YES	24 - 28s	27 - 28.6s	45 - 49s	ND
11	YES	8 - 12s	11.8 - 12.2s	63 - 67s	66.6 - 67.6s

ND: Not Detected

7. Conclusion

- Device - 2 / 2
- Pinch Detect - 4 / 11
- Clap Detect - 7 / 11
- Error Correction - 4 / 11

REFERENCES:

[1] Martini, Frederic; Bartholomew, Edwin (2001). *Essentials of Anatomy & Physiology*. San Francisco: Benjamin Cummings. p. 263. ISBN 0-13-061567-6.

[2] http://www.ncbi.nlm.nih.gov/pubmed/18473082

[3] Sara Taylor , Natasha Jaques, Weixuan Chen, Szymon Fedor, Akane Sano and Rosalind Picard, "Automatic Identification of Artifacts in Electrodermal Activity Data"

[4] Serhat ALADAĞ, Ayşegül GÜVEN, Hatice Özbek, Nazan DOLU, "A Comparison of Denoising Methods for Electrodermal Activity Signals"

[5] J. Schumm, M. Bächlin, C. Setz, B. Arnrich, D. Roggen, G. Tröster, "Effect of Movements on the Electrodermal Response after a Startle Event

[6] http://www.birmingham.ac.uk/Documents/college-les/psych/saal/guide-electrodermal-activity.pdf

[7] https://docs.scipy.org/doc/numpy/reference/

[8] http://matplotlib.org/api/pyplot_api.html