Brain Activity and Healthcare in the Smart Home

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***Abstract*—A step towards improving living standards for elderly and patients is to incorporate healthcare systems in the home. Aiming to increase the safety and independence of these groups this paper highlights a few possible approaches. Specifically the focus has been on; fall detection using the Electroencephalography(EEG) sensor Emotiv EPOC, a monitoring and drug administration system, a control system for home appliances based on EEG and sleep improvement with EEG in the smart home.**

A fall detection study has been performed, determining whether a fall can be differentiated from similar events. The study concludes that EEG sensors might have potential as part of a fall detection system. The remainder of the project is theoretical. It holds potential, however experiments need to be performed for further conclusions.

***Index Terms*—EEG, EPOC, control system, drug administration, sleep improvement, detection theory.**

I. Introduction

THE smart buildings consist of sensors monitoring the building as well as its residents. The development of them creates new opportunities for a higher standard of living, characterized by a safer and more comfortable living environment. Healthcare systems integrated into homes are an example of such opportunities. The main focus group, here, is elderly and patients at home. Introducing healthcare systems into homes will allow patients and the elderly, who would otherwise be treated in specialized institutions, to get their treatment in the convenience of their homes.

In the future, smart buildings integrated with healthcare systems might be the standard. However, before this could be reality, more research and technical development are needed, outlined by [1]. There are multiple factors which might affect the rate of this development. For example, building smart homes from scratch, instead of transforming them later on, will be an accelerator to the progress. Another factor would be to show the improvement on safety concerns through integrated healthcare systems at home. Falls are one of the most common reasons people over the age of 65 end up in the emergency room. The risk of a fall and the injuries that might follow increase with age, and, are the main cause for admission to nursing homes [2]. Finding a way to detect falls and alarm caretakers would not only improve the patients' safety but also be economically favourable since the need of nursing homes would decrease.

Another reason why patients might be admitted to nursing homes is to decrease the risk of them not taking their medicine. In a smart building, the use of a smart medicine cabinet and a smart bracelet would make sure that the caretaker would be informed if the right amount of medicine were not consumed. Furthermore, smart buildings may help the mobility disabled to control their equipment. For instance wheelchairs are currently controlled by patients' hand movements, but there is research on the potential of doing it by using facial expression [3]. This would allow paralyzed patients without hand-mobility to move around without external help.

Furthermore, the healthcare systems yield the possibility of a continuous monitoring. Instead of a patient visiting a doctor regularly, the health condition of the patient could be sent to the caretaker at all time. Medicine dosage could be based on more recent measurements. This would decrease the risk of both overdoses and shortage of medicine.

Finally, sleep is of great importance for health status. The amount of time spent sleeping as well as the efficiency and quality of it affect both physical and mental health. Improving sleep would therefore increase the quality of life. Such an improvement can be achieved using healthcare sensors.

There are several types of wearable sensors readily available at the market. Among them are some developed to be less expensive which would be appropriate for the smart building. One example of this is EPOC, an Electroencephalography(EEG) sensor by Emotive [4]. In this paper, we investigate the possibility of using EPOC to detect a fall. After presenting some background information about the sensor and detection theory applied on the experimental data in section II, we proceed by presenting our method in section III, where we outline our experiment. The result is given in section IV and discussed in section V. Moreover, in section V, we describe a system for drug administration and monitoring, propose a control system based on EEG, and finally, discuss the potential of using healthcare sensors to improve sleep quality. We finalize the paper with concluding remarks in section VI.

II. Background

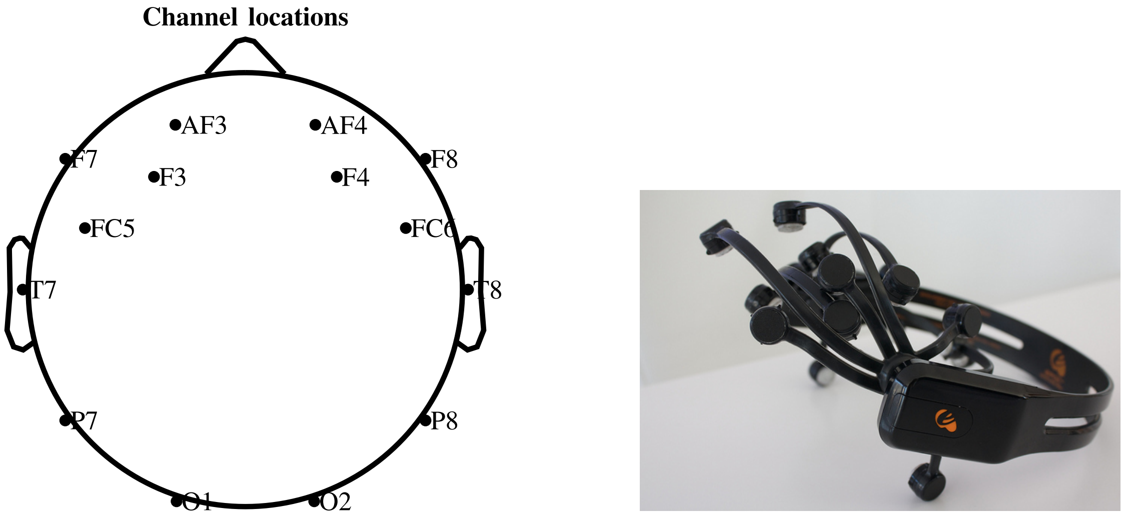
A. EPOC

Emotiv EPOC is an EEG sensor which is made to be cheap and usable outside laboratory environment, and therefore, is of possible interest in a smart building.

The sensor has 14 electrodes, i.e. channels, to be used for measurements on the positions indicated in Figure 1, and, 2 nodes to be used as references between the t and p channels [4]. It is wireless and uses Bluetooth to transmit the signals to a computer with a sampling rate of 128 Hz. A lithium based battery provides EPOC with 12 hours continuous usage. Beyond the EEG sensors, EPOC also contains a gyroscope [5].

B. Detection Theory

In a detection study, several trials are performed; some with noise, others with a signal of interest. Deciding whether the signal occurred or not results in four possible outcomes, as shown in Table I.



(a) Positions of the electrodes/channels

(b) Emotiv EPOC [6]

Fig. 1. The EEG sensor Emotiv EPOC

TABLE I
TABLE SHOWING THE POSSIBLE OUTCOMES IN A DETECTION STUDY.

	Yes	No
Noise	False Alarm	Correct Rejection
Signal	Hit	Miss

Using these outcomes together with (1) and (2), a false alarm rate (f) and a hit rate (h) can be calculated.

$$f = \frac{\text{number of false alarms}}{\text{number of noise trials}} \tag{1}$$

$$h = \frac{\text{number of hits}}{\text{number of signal trials}} \tag{2}$$

The amount of evidence during a trial is described by a random variable X, as shown in Figure 3. Random variables X_n and X_s represent the noise and signal evidences, respectively. The density and cumulative distribution functions are denoted by $f_n(x)$ respectively $F_n(x)$ for the noise and $f_s(x)$ respectively $F_s(x)$ for the signal. The criterion λ is used as a threshold to determine the amount of evidence needed for accepting or rejecting an event, as illustrated in Figure 6.

X can, with good accuracy, be estimated to be a Gaussian distribution:

$$X_n \sim N(\mu_n, \sigma_n^2),\ X_s \sim N(\mu_s, \sigma_s^2). \tag{3}$$

Here, the relative values of σ_n and μ_n with respect to σ_s and μ_s are more important than their exact values. One convention to decide on the values of these parameters is to assume that the noise has a standard Gaussian distribution, i.e. $X_s \sim N(0,1)$. This leaves μ_s, σ_s^2 and λ to be determined. However, one needs an additional assumption, as h and f are not enough alone to determine these three parameters. The additional assumption comes from the *equal variance model*, in which the variance of the signal is assumed to be $\sigma_s^2 = \sigma_n^2 = 1$. In this standard approach, $\mu_s = d'$ gives

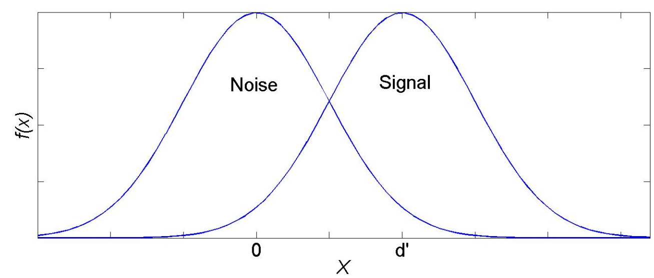


Fig. 2. Gaussian distributions centred in d' and the origin.

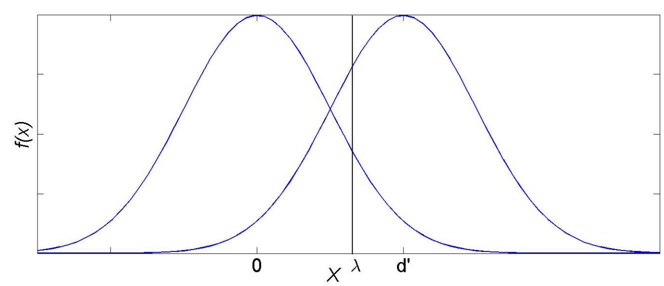


Fig. 3. The criterion λ is used as a threshold. All evidences X to the right λ will receive an affirmative answer.

the distance between the noise and the signal distributions, as shown in Figure 2. The equal variance model yields the following:

$$X_n \sim N\left(0,1\right),\ X_s \sim N\left(d',1\right). \tag{4}$$

The probability of an evidence being greater than the criterion is denoted by $P(X > \lambda)$. Probabilities for false alarms and hits are calculated by (5) and (6), respectively:

$$P_F = P(X_n > \lambda) = \int_{\lambda}^{\infty} f_n(x)dx = 1 - F_n(\lambda), \tag{5}$$

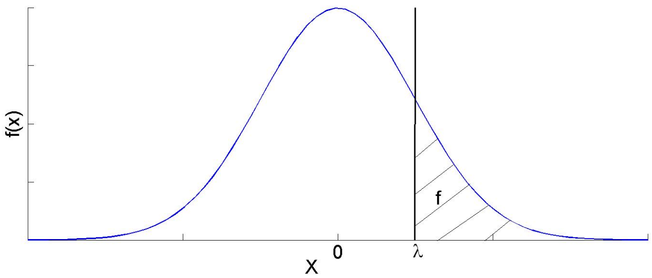


Fig. 4. Relation between f and λ is displayed.

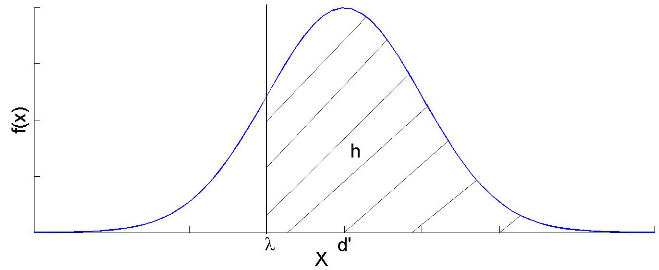


Fig. 5. Displays relation between h, λ and d'.

$$P_H = P(X_s > \lambda) = \int_{\lambda}^{\infty} f_s(x)dx = 1 - F_s(\lambda). \quad (6)$$

For Gaussian distributions, both density ($f(x)$) and cumulative distribution ($F(x)$) functions can be calculated from the standard Gaussian distribution, i.e. $N(0,1)$. For a standard Gaussian distribution, these functions are defined as given in equation 7:

$$\begin{aligned} f(x) = \phi(x) &= \frac{1}{\sqrt{2\pi}} \mathrm{e}^{-x^2/2}, \\ F(x) = \Phi(x) &= \int_{-\infty}^{x} \phi(z)\, dz. \end{aligned} \quad (7)$$

$f(x)$ and $F(x)$ for non-standard Gaussian distributions are calculated by simply normalizing the random variable x as in 8:

$$\begin{aligned} f(x) &= \phi\left(\frac{x-\mu}{\sigma}\right), \\ F(x) &= \Phi\left(\frac{x-\mu}{\sigma}\right). \end{aligned} \quad (8)$$

Thus, (5) and (6) can be re-written as (9) and (10), respectively:

$$P_F = 1 - F_n(\lambda) = 1 - \Phi(\lambda), \quad (9)$$

$$P_H = 1 - F_s(\lambda) = 1 - \Phi(\lambda - d'). \quad (10)$$

Now, estimates $\hat{\lambda}$ and $\hat{d}'$ of λ and d', respectively, can be obtained by using f and h. $\hat{\lambda}$ is the point on the noise distribution at which the probability of false alarms is computed, as displayed in Figure 4. The estimate $\hat{\lambda}$ can be obtained by using the inverse of $\Phi(x)$ (in equation 9), denoted by Z, as follows:

$$\hat{\lambda} = Z(1-f), \quad (11)$$

where $Z(y)$ can be obtained by using tabulated data for y.

Similarly, the probability of hits (h) is computed by using $\hat{\lambda}$ on the signal distribution, as displayed in Figure 5. Hence, the center of the signal distribution (d') is obtained by using (10), (11) and the symmetry of Gaussian distributions as follows:

$$\begin{aligned} \hat{d}' &= \hat{\lambda} - Z(1-h), \\ &= \underbrace{Z(1-f)}_{-Z(f)} - \underbrace{Z(1-h)}_{-Z(h)}, \\ &= Z(h) - Z(f). \end{aligned}$$

To quantify the quality of the detection, the bias is calculated. The bias, β, describes whether the detection method accepts or disregards the signal. It is defined as the first step in equation 12, where equation 7 has been used to simplify the calculations:

$$\beta = \frac{f_s(\lambda)}{f_n(\lambda)} = \frac{\phi(\lambda - d')}{\phi(\lambda)} = \mathrm{e}^{-d'\left(\frac{d'}{2} - \lambda\right)}, \quad (12)$$

The value of β will determine if more acceptances or rejections are favoured as given in (13):

$$\beta \begin{cases} = & \text{no preference} \\ < 1 & \text{more acceptances} \\ > 1 & \text{more rejections} \end{cases} \quad (13)$$

However, this results in an asymmetrical dependency, since β ranges from 0 to ∞. This problem is resolved by taking the natural logarithm of β:

$$\ln \beta = d'\left(\lambda - \frac{d'}{2}\right). \quad (14)$$

Now, the probability of correct prediction, P_C, can be calculated. Here, there are two options: either the value of different outcomes can be included, or, focus could be strictly on the detection result. In the latter, the function to maximize is plotted in Figure 6 and defined as below:

$$\begin{aligned} P_C &= P(\text{signal + yes}) + P(\text{noise + no}) \\ &= P(\text{signal})P(\text{yes}|\text{signal}) + \\ &\quad P(\text{noise})P(\text{no}|\text{noise}) \\ &= sP_H + (1-s)(1-P_F) \\ &= s(1-F_s(\lambda)) + (1-s)F_n(\lambda), \end{aligned}$$

where s is the probability of the signal occurring.

The function is maximized by setting the differential with respect to λ to zero, which yields:

$$\frac{f_s(\lambda^*)}{f_n(\lambda^*)} = \frac{1-s}{s}. \quad (15)$$

Combined with equation 12 and 14, the above equality gives the following:

$$\ln\left(\frac{1-s}{s}\right) = d'\left(\lambda^* - \frac{d'}{2}\right). \quad (16)$$

In a study with equal amount of noise and signal trials, the probability of the signal occurring is $s = 1/2$. The optimal criteria, λ^*, is thus obtained as: $\lambda^* = \frac{d'}{2}$.

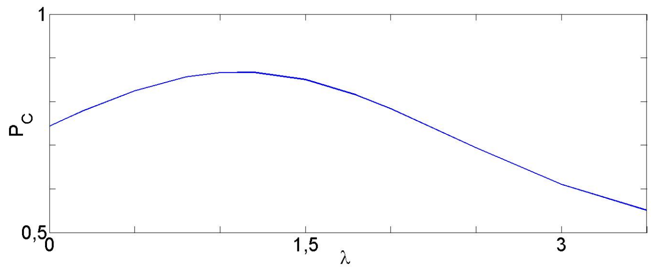


Fig. 6. The probability of correct prediction P_C for different λ where d' is held constant .

If the value of the outcomes are included instead, the function to optimize becomes $E(V)$:

$$\begin{aligned} E(V) &= P(\text{signal + yes})V(\text{hit}) + \\ & P(\text{signal + no})V(\text{miss}) + \\ & P(\text{noise + yes})V(\text{false alarm}) + \\ & P(\text{noise + no})V(\text{correct rejection}), \end{aligned}$$

where V is the value of each outcome, i.e. the gain. Optimizing $E(V)$, using the same method outlined above, λ^* is obtained as follows:

$$\begin{aligned} \lambda^* &= \frac{\log(c_f/c_m)}{d'} + \frac{d'}{2}, \\ c_m &= V(\text{hit}) - V(\text{miss}), \\ c_f &= V(\text{correct rejection}) - V(\text{false alarm}). \end{aligned}$$

The detection theory summarized in this section follows from [7].

III. METHOD

A. Detecting a fall

One purpose of this study is to determine if it is possible, using Emotiv's EPOC to differentiate between a fall and a seemingly similar event. "Similar'" here, is defined as something that would produce similar gyroscopic data- the idea being that in order to detect a fall, one should differentiate among events having comparable gyroscopic signals.

60 trials have been performed with one subject. The subject was instructed to "fall" 30 times. The fall action consists of the subject voluntarily leaning backwards until being caught. likewise the subject is instructed to sit down 30 times. During each trial, EEG and gyroscope data are gathered using EPOC,and, and using a stopwatch, the time at which each event begin is recorded. The number of trials is based on [8].

Collected data are processed using EEGLAB, an extension to MATLAB. 5-second-long epochs, starting 1 second before the command is given, are extracted from the data. The average of the first second in this interval over all experiments is used as a baseline. Each channel is analysed separately. Patterns of the EEG signals differentiating the two events, are determined for each channel. In each trial, each channel is then given an affirmative ("yes") or a negative ("no") answer depending on if the pattern has occurred. Moreover, every trial is given a final yes or no, which may be defined as the average answer when all the channels have been considered, i.e. yes if more than half of the channels have been assigned yes.

Finally, taking into account the final answers, the false alarm and hit rates are calculated using the detection theory outlined in section II-B.

IV. RESULT

A. Detecting a Fall

Criteria used to detect the fall for each channel can be found in Table II. Concerning the evaluation of the fall trials, it is only of interest to look at the first ~ 2 seconds, since the rest of the data is similar to that after being caught.

It is worth noting that almost all conditions are of the type "not below" some threshold. This is because the subject "sitting down" has resulted in higher amplitude signals than those resulted from the "falling", which can be observed in Figure 7.

Different f and h values for each channel as well as their final values can be found in Table III. The values are calculated using (1) and (2). The final yes or no was defined as the average answer when all the channels were considered, i.e. yes if more than half of the channels were assigned yes.

TABLE II
TABLE SHOWING THE CONDITIONS USED FOR DIFFERENTIATING BETWEEN EVENTS

Channel	Condition to be classified as a fall
AF3	250 ms of a clear positive trend
AF4	No discernable pattern
F3	Not a clear negative trend for more than 500 ms
F4	Not a potential below -250 μV for over 300 ms
F7	Not a long trend over 300 μV
F8	Not a potential below -300 μV for 500 ms in the timespan 1000-2000 ms
FC5	Not a potential below -150 μV for 300 ms in the timespan 0-1200 ms
FC6	Not a potential below -500 μV for 300 ms
O1	Not a potential below -300 μV for 300 ms
O2	Not an absolute value of potential above 250 μV for 300 ms
P7	Not potential pot below -300 μV for 300 ms
P8	Not potetial below -300 μV for 300 ms
T7	Not a potential below -400 μV for 300 ms
T8	Not quickly switch between -300 and 300 μV or more

Applying the detection theory outlined in section II-B on the experiment data yields the final false alarm and hit rates from equations 1 and 2:

$$f = 0.133, \ h = 0.867 \tag{17}$$

whereas individual channel readings can be observed in Table III.

Following the remaining steps, the criteria λ, and, the offset d' between the noise and signal distributions can be estimated. These estimates can then be used to calculate the probability of a correct prediction, P_C. Results of the calculations are as follows:

$$\begin{aligned}
\hat{\lambda} &= Z(1-f) \\
&= Z(0.867) \\
&= 1.113, \\
\hat{d}' &= Z(h) + Z(1-f) \\
&= 2.226, \\
P_C &= \frac{1}{2}\left(1 - \Phi(\hat{\lambda} - \hat{d}') + \Phi(\hat{\lambda})\right) \\
&= \frac{1}{2}\left(1 - \Phi(-1.113) + \Phi(1.113)\right) \\
&\quad \{1 - \Phi(-x) = \Phi(x)\} \\
&= \Phi(1.113) \\
&= 0.867.
\end{aligned}$$

Note that the estimated criterion $\hat{\lambda}$ is equal to half of the estimated d'. As described in Section II-B, this is the optimal criterion in a study with equal amount of signal and noise trials.

TABLE III
TABLE SHOWING THE DIFFERENT f AND h FOR EACH CHANNEL.

Channel	f	h
AF3	0.333	0.8
AF4	-	-
F3	0.267	0.833
F4	0.233	0.9
F7	0.1	0.6
F8	0.233	0.867
FC5	0.3	0.933
FC6	0.133	0.9
O1	0.133	0.9
O2	0.2	0.867
P7	0.167	0.867
P8	0.333	0.9
T7	0.267	0.833
T8	0.133	0.867
Final	0.133	0.867

V. DISCUSSION

In this section the result of the detection study as well as potential drug administration and control systems are discussed. Finally the possibility of improving sleep quality, using EEG is considered.

A. Detecting a Fall

In order to detect a fall, different activities with similar gyroscopic signals must be differentiated. The amount of random activity in the brain necessitates a large amount of trials to detect a pattern with reasonable certainty. This study, therefore has focused on detecting a certain type of fall in comparison to a specific activity - namely someone sitting down on a chair.

Standard procedure in studies concerning EEG is to either apply a band pass filter to allow the 1-30 Hz range while suppressing the frequencies not associated with brain-activity, or, to use an individual component analysis (ICA) technique to remove artifacts [9]. In the context of this study, it is not necessary to detect a fall using brainwaves. Thus, all frequencies are of interest and a band pass filter is not applied.

The analysis of patterns is conducted visually using event related potentials (ERP) plots. An example can be seen in Figure 7. Where each horizontal line corresponds to a trial, and, the color gradient maps measured potentials at a given time. This type of analysis naturally has got some flaws. Such as the visual inspection as to if a pattern occurs in a trial. Furthermore the experiment has been conducted with only one subject, which means that universal conclusions cannot be drawn.

ERPs are mostly used in experiments where it is clear when an event occurs, and therefore, when the brain responds [8]. This is not the case in this fall detection study. The data in the fall detection study is skewed in each trial. This means that trends and patterns of higher frequencies are not possible to detect in the averaged data, seen in the graph below the ERP in Figure 7. The data is skewed because, it is unclear when during the fall one is to expect the brain to respond, and, the falls have unequal times spans.

No analysis regarding if the two events has the same gyroscopic signal was conducted. The conclusion regarding the similarity of the gyroscopic signals of the two events, when designing the experiment, has solely been the product of the authors speculation.

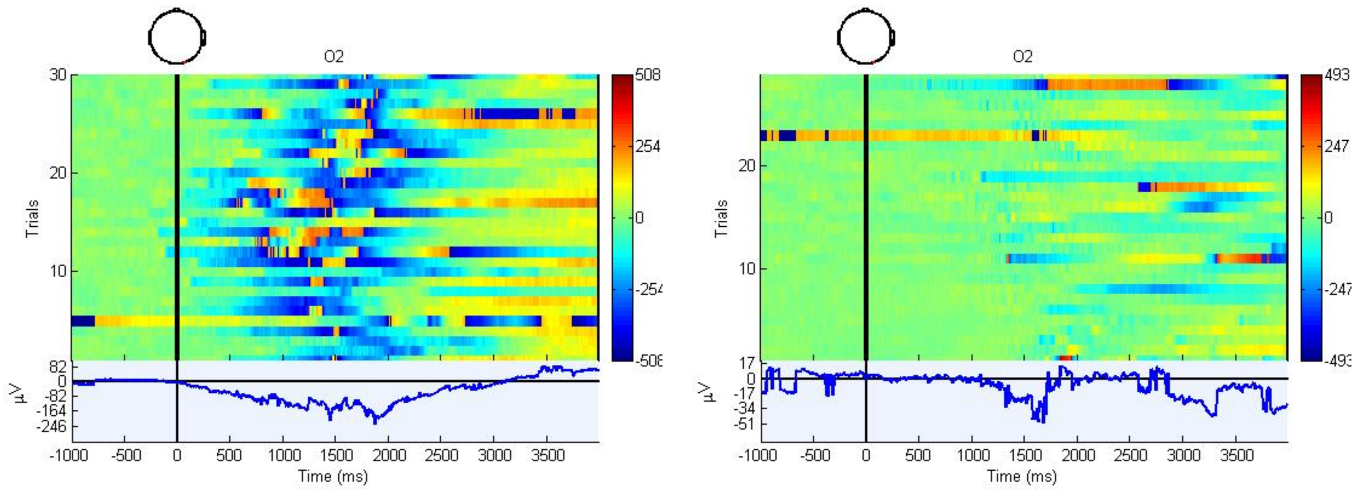
Still this study show promising indications that a fall detection system might be possible to implement using a low budget EEG sensor such as EPOC. This could allow for patients to a higher degree to be treated at home remotely since a system automatically could send an alarm if a fall was detected. But to reach that point more research is needed concerning different subjects and diverse activities.

One can observe from Table II that sitting down generally has caused higher amplitude signals than those the falling has caused. This might be due to artifacts from muscle usage while sitting down, and the lack thereof when falling limply backwards. This hypothesis calls for the testing of falls wherein the subject tries to catch themselves, as well as the testing against different movements, with possibly fewer muscle artifacts, which cause similar gyroscopic outputs.

B. Monitoring System and Drug Administration

One of the goals with the project was to design a sensor system to monitor patients and administer medicine. The system should manage tasks such as obtaining medical information from the patient, administer drugs, updating a doctor of the status and monitor the amount of medicine available.

To obtain the present state of the patient, sensors would be used. There are several wearable, practical sensors available today, some that could be interesting for health monitoring can be found in Table IV. Possible data, which could be retrieved by using the sensors, are brainwave patterns, heart-activity,



(a) Sitting down

(b) Falling

Fig. 7. ERP image for the channel O2 during the sitting down (a) and fall (b) events. Each horizontal line corresponds to a trial, and the colour to the measured potential at that point in time using the unit μV. The plot underneath the ERP plot is of the average signal.

blood-values and positions. The doctor would decide which of the data that would be interesting, depending on the patient. For instance; a patient with a heart disease would wear an Electrocardiography(ECG) sensor while Electroencephalography(EEG) could be used to monitor epileptic seizures or discovering brain-tumours.

The sensors would use WiFi to send the obtained information to a computer, which would automatically run a program using the information as input. The program has knowledge of an optimal state which the patient should be in as well as information of how the available medicine would affect the state. It would then calculate the amount of medicine which should be given to the patient to reach the optimal state. The concept of the program is easy but becomes more complicated because of time-delay and the medicines multiple effects. Most medicines do not have an instant effect. Therefore there is a risk that the program uses input obtained in a time-interval when medicine has been distributed but not yet given affect. As a result this could lead to the program distributing to much medicine. To prevent this, the time it takes from the medicine being consumed until the affect is shown, can be incorporated in the system. One option is to put a time-lock on the drug administration, making it impossible for the program to distribute the certain types of medicine until a specific time has passed. When the lock is opened again only drug distribution based on new input would be executed, i.e. information recorded during the time-lock would not be used in drug administration. Furthermore the system needs to take all the medicines effects into account. Since medicine normally has both positive and negative affect there is a risk of harming the patient if only one aspect is considered. However this problem could be solved by using a similar solution as for the time-delay. Assuming the doctor is aware of the negative affect the medicine could have and at which concentration this becomes a problem, a maximum dose/time could be decided. As with the time-delay a lock is put on the medicine when the maximum is reached and opened when enough time has passed. Furthermore the computer forward all the information to a doctor. The doctor then monitor the patient from a distance. A first step in the development of the system is to include the doctor in a wider range and exclude the part of the program calculating the medicine to distribute. The doctor would then decide the drug administration based on the received data.

The next question is how the system should use the output from the program or the doctor. This would once again depend on the patient. There are two main possibilities of the actual consumption of the medicine; pills or injections. Both of which have advantages and disadvantages. Pills are more practical for a mobile patient and more comfortable, not involving a needle. Injections however reach the bloodstream directly which gives a better and faster effect. Furthermore injections could be controlled using a digital mechanism, with the needle in place at all time and medicine distributed directly by the program. This would be similar to how diabetes medicine is distributed today according to [21]. However it could also be seen as a disadvantage since it eliminates the patients free choice of taking the drug in the specific moment. It might also be hard and dangerous for the patient to carry. The injections might therefore not be the best option if the patient is mobile. Considering paralysed patients the injections could be practical, since no other person is needed to handle the drugs. In the rest of this report focus will be on pills.

Considering the pills, the task of the system would be to communicate to the patient when and what amount of medicine should be consumed. This can be done using a bracelet which the patient wears. The bracelet receives signals from the computer and an alarm goes off when drugs should be consumed. The bracelet also gives the patient information of the amount and type of medicine, this would be shown on a display.

The system should ensure that the caretaker is notified if

TABLE IV
HEALTHCARE SENSORS WHICH HAVE POTENTIAL OF BEING USEFUL IN A SMART HOME.

Sensor	**Output data**	**Possible use of data**	**Sensor on the market**
EEG	Brain activity	Monitor patient, detect seizures or tumours, control equipment	EPOC [4]
EMG	Muscle activity	Control equipment	Shimmer [10], Biometrics Ltd [11]
ECG	Heart activity	Monitor patient, detect heart-diseases	Shimmer [10], EPIC [12]
Gyroscope	Position	Monitor patient movement	Bosch BMG160 [13]
Accelerometer	Position	Monitor sleep and/or movement	Apps for smart phones, LG smart activity tracker [14], fitbit [15], sleepcycle [16]
Carbon dioxide sensor	Carbon dioxide concentration in human respiration	Monitor respiratory capability	SprintIR 20Hz 5-100% CO2 Sensor [17]
Oxygen saturation sensor	Oxygen saturation in blood stream	Monitor respiratory capability	iHealth [18], SPO2 [19]
Blood pressure sensor	Blood pressure	Monitor cardiac capability, detect sudden drops or peaks	iHealth [18],
Stress sensor	Level of stress hormones in sweat	Monitor patient	Neumitra [20]

the right amount of medicine is not consumed. This could be done by using a smart medicine cabinet. The cabinet contains different compartments; each containing one type of medicine. The cabinet would function as a vending machine. However, instead of the patient choosing what medicine to obtain the machine receives information from the computer. The information would include type of medicine and amount. When medicine has been distributed the patient simply press a button and the medicine is obtained. The patient can then compare the given dose with the information on the bracelet. This should of course match. If medicine is not retrieved within a certain time-interval the caretaker is notified. The smart medicine cabinet would decrease the risk of the patient consuming inaccurate type and amount of medicine and ensure that the caretaker has knowledge of whether the distributed medicine is retrieved.

However, the fact that medicine has been retrieved dose not ensure that it has been consumed. One possibility is to use Radio Frequency Identification Device(RFID) chips [22]. The chips are ingestible trackers. Each pill contains a chip which transfer unique signals withholding information of type and dose of medicine. A RFID-receiver is implanted and will detect signals from the chip when consumed. The information is then forwarded to the computer. Two types of RFID-chip are possible to use; those which include batteries and those which does not. Those with batteries would transfer signals at all time while the other type, powered by the receiver through low frequency signals, would transfer when power is available. This system would use the second type to prevent unnecessary signals being sent. If retrieved medicine is not consumed within a certain time-interval the caretaker is notified.

Furthermore the medicine cabinet would keep track on the amount of medicine available. Each compartment of medicine consists of a container where the pills are filled up and a wheel with holes the size of a pill. The wheel would be placed with all but one of the holes beneath the container. The last hole would be placed above a tube. A cut disc would be placed beneath the part of the wheel at the bottom of the container. As a result the holes beneath the container would at all time contain one pill each, while the last hole would be empty. When a pill is to be retrieved the wheel would spin, resulting in a pill falling down the tube. The tube would lead to a bowl where the patient can obtain the pills. This is displayed in figure 8. The mechanism yields a possibility to notify the patient and caretaker when the pills are running low. Sensors in the holes detect whether a pill is present or not. When the wheel is no longer full, i.e. when not all the holes beneath the container contain a pill, the computer is notified. By designing the wheel to a appropriate size the minimum amount of pills before a notification is sent can be determined.

The system would provide the patient with information of what medicine to take, when to take it and when to obtain new medicine. It would also forward information of the patients state to a doctor and notify the caretaker if the right amount of medicine is not consumed.

C. Control System

One of the questions raised in this project is whether EEG can be used to control household equipment. By analysing the brainwaves measured with the EEG sensor, patterns can be detected from certain events. For instance blinking results in a specific pattern. These patterns can be determined by repeatedly performing the event and recording it. Event-studies with EEG, i.e. determining brainwave patterns for specific events, have been executed for several events. The Emotiv software include three suits; expressive, affective and cognitive [4]. The expressive suit detects facial expressions, while the affective detects emotions and the cognitive detects thoughts of movement (left, right and so on). While experimenting it was concluded that the cognitive suit was less reliable and more difficult for the subject. Furthermore emotions might be hard for a subject to control. Therefore the software used in a

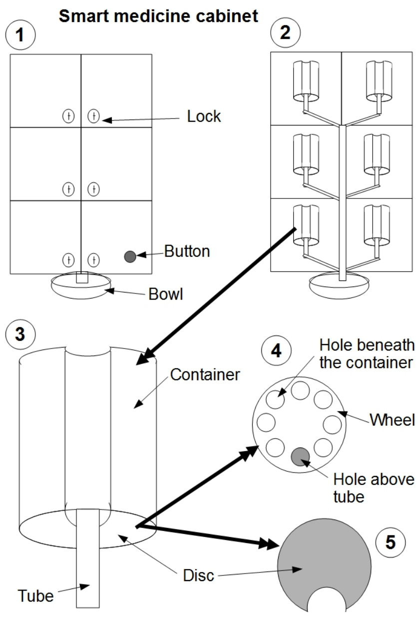


Fig. 8. Graphic description of the smart medicine cabinet. 1 shows the patients view. 2 show the inside of the cabinet with the different compartments. 3 is an enhancement of a compartment and display the shape of the container and its position above the tube, disc and wheel. 4 display the design of the wheel and finally 5 show the shape of the disc, which is the same shape that the container has seen from above.

control system should use an expressive suit and detect facial expressions.

The EEG sensor records brainwaves and sends the signals through WiFi to a computer. A software, using an expressive suit, then detects events. Finally, events is linked to actions such as turning on a light or lowering the sound of a stereo. The entire system would work as follows. First, an event occur, for instance the subject blinks. Second, the computer receives the EEG-signals from the sensor. Now, the software will analyse the signals and detect the specific events, i.e. the facial expressions. When the software has detected and identified the event, it sends a signal to the equipment being controlled. Finally, the equipment performs the action specified by the signal.

To decrease the risk of misdetection the patterns of the events should be personal. EEG signals are specific for each person and the same event might not correspond to the same exact pattern for two different subjects. This follows from [23]. How much the pattern deviate from the average will vary. Therefore, the events used as signals should be trained, i.e. performed repeatedly until a personal average has been established. This will increase the accuracy of the system.

It is however impossible to create a system which would predict each event/non-event perfectly with an absolute certainty. Therefore, the system should not be used to control equipment which, with inaccurate control, could cause sever consequences.

Finally, muscle movements cause disturbance in the EEG signals. The noise created by the subject moving can in some extent be removed by eliminating signals of frequencies outside the interval of brainwaves. However it might not be possible to remove all the noise. When using EEG in studies and in hospitals the subject is most often still. Another way of improving the accuracy is therefore to control equipment while not moving. This would demand that the equipment being controlled allows the subject to be still. One potential application would be a paralysed person controlling a smart wheelchair. This would demand a high probability of correct prediction to assure a low risk of accidents. The next step in the development is to perform experiments. This has been done by others in some extension [24]. Further work in this field as well as development of affordable, quality sensors will allow the control system to be reality in the future.

D. New Application

There are many possibilities of using healthcare sensors in the home. Using EEG, the mind can be mapped, determining how outer stimuli affect subjects. Analyzing which frequencies dominate the brainwaves, the state of mind (sleeping, focused, awake and aware) can be determined. A higher awareness correspond to brainwaves dominated by a higher frequency. Brainwaves are classified as β, α, θ and δ waves according to table V. While all frequencies can occur in every state of mind a specific type usually dominates. α correspond to a subject with closed eyes, focusing on being calm. β on the other hand corresponds to a normal awake state, where the subject is being affected by the surrounding. Finally θ and δ dominates in sleep according to [25]. This indicates that EEG signals could be used to determine the depth of sleep.

Being awakened while in deep sleep will cause the subject to feel non-rested. Fewer hours of sleep will result in a more well rested experience if the subject is closer to awareness when the awakening is performed. Optimizing the awakening with regard to the sleep stages would therefore lead to a more effective sleep.

EEG sensors could be used during sleep to determine the dominating frequencies of the brainwaves. Hence creating an optimal alarm. Based on a determined time-interval for when to wake up the system could optimize the time according to the EEG signals. Alarms similar to this are already available as applications in smart phones, these alarms use accelerators to determine the sleep stage. An example of this is [16]. Using EEG instead could however yield more possibilities discussed below. Determining the optimal time to awake could be done by using a minimum frequency for which the alarm is allowed to go off. The EEG would start measuring the brainwaves when the time-interval begins. When the minimum frequency is reached the alarm goes off. If the minimum frequency is not reached within the interval the alarm goes off at the end of it. The minimum frequency should be optimized. This might be done by measuring the frequencies during the entire night and then using one of the higher frequencies as the minimum. The minimum would then be adjusted to the night in question.

Furthermore EEG might be used to optimize how the awakening is being performed. By analysing how the state of mind of a subject is affected by different outer stimuli an optimal alarm might be determined. Experiments with the subject listening to different types of sounds and being exposed to various light settings could be performed to determine which result in a calm or agitated state. However, deciding which state would be preferred remains. An agitated state would increase the chance of the subject awakening. While a calm state probably would be more comfortable. To determine the optimal state tests should be performed. The optimal state is most likely somewhere in between the two extremes. One possibility is to combine the alarm with the drug administration system described in section V-B and use the bracelet. The bracelet could then vibrate, light up or play music according to the result of the experiments.

Moreover, the recorded brainwaves could be used to analyse the subjects sleep. The settings during sleep could then be optimized in the same way as the alarm.

Thus, EEG might be used to optimize sleep, both by creating the optimal settings as well as determining when and how the subject should awaken.

TABLE V
CLASSIFICATION OF BRAINWAVE FREQUENCIES.

Class	δ	θ	α	β
Frequency (Hz)	$0.5 - 4$	$4 - 8$	$8 - 13$	> 13

VI. CONCLUSION

The experiment provides promising indications that a fall detection system using a low budget EEG sensor, such as EPOC, might be implementable. The logical next step is to investigate fall detection concerning different subjects and diverse activities. Especially investigating falls wherein the subject is trying to catch themselves are of interest. This to test the hypothesis outlined in Section V-A.

Regarding the theoretical system for drug administration, conclusions can not be made concerning its reliability. To determine if the described system has any potential practical implementation need to be performed. Based on theory the control system seem to be applicable. However, due to the absence of experimentation no further conclusions will be drawn in this paper.

Improving sleep quality by optimizing the time for awakening as well as the actual sleep is already being implemented. Whether EEG would be a good instrument in this development can not be concluded. In theory it shows potential and experiments should be performed to draw further conclusions.

Incorporating a healthcare system in the home could potentially result in a safer, more comfortable life. However, practical tests need to be performed and further development of affordable sensors need to be achieved before it can be reality.

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REFERENCES

[1] M. Alam, M. B. I. Reaz, and M. A. M. Ali, "A review of smart homes x2014;past, present, and future," *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, vol. 42, no. 6, pp. 1190–1203, Nov 2012.

[2] M. E. Tinetti and C. S. Williams, "Falls, injuries due to falls, and the risk of admission to a nursing home," *New England Journal of Medicine*, vol. 337, no. 18, pp. 1279–1284, 1997, pMID: 9345078. [Online]. Available: http://www.nejm.org/doi/full/10.1056/NEJM199710303371806

[3] P. Faria, R. Braga, E. Valgode, and L. Reis, "Interface framework to drive an intelligent wheelchair using facial expressions," in *Industrial Electronics, 2007. ISIE 2007. IEEE International Symposium on*, June 2007, pp. 1791–1796.

[4] E. corparation, "Epoc features," March 2014. [Online]. Available: www.emotiv.com/

[5] M. Duvinage, T. Castermans, M. Petieau, T. Hoellinger, G. Cheron, and T. Dutoit, "Performance of the emotiv epoc headset for p300-based applications," *Biomedical Engineering OnLine*, vol. 12, pp. 56 (15 pp.) –, 2013//, emotiv Epoc headset;P300-based application;EEG-based Brain-Computer Interface systems;out-of-the-lab application;medical-grade EEG recording device;disabled people;medical-grade system;ANT device;P300 BCI;biomedical electrode;review;sitting;walking;high relative operational;maintenance costs;low-cost headset;EEG data recording;game;communication system;rehabilitation;prosthesis control;medical system;Signal-to-Noise Ratio;specific low-cost EEG recording system;. [Online]. Available: http://dx.doi.org/10.1186/1475-925X-12-56

[6] D. Bakker, "Emotive epoc," 2010. [Online]. Available: https://www.flickr.com/photos/drbakker/4540124047/in/photolist-

[7] T. D. Wickens, *Elementary Signal Detection Theory*. Oxford University Press, USA, October 2001.

[8] M. Rugg, "Event-related potentials (erps)," in *Encyclopedia of Neuroscience*, L. R. Squire, Ed. Oxford: Academic Press, 2009, pp. 7 – 12. [Online]. Available: http://www.sciencedirect.com/science/article/pii/B978008045046900752X

[9] D. Djuwari, D. Kumar, and M. Palaniswami, "Limitations of ica for artefact removal," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, Jan 2005, pp. 4685–4688.

[10] Shimmer, "Products," April 2014. [Online]. Available: www.shimmersensing.com/

[11] B. Ltd, "Surface emg," April 2014. [Online]. Available: www.biometricsltd.com/

[12] P. semiconductors, "Epic is plessey's multi award winning sensor," April 2014. [Online]. Available: www.plesseysemiconductors.com/

[13] Bosch, "Bosch sensortec," April 2014. [Online]. Available: www.bosch-sensortec.com/

[14] LG, "Fitness and activity tracker," April 2014. [Online]. Available: www.lg.com/

[15] fitbit, "Products," April 2014. [Online]. Available: www.fitbit.com/

[16] A. Northcube, "Sleep cycle," April 2014. [Online]. Available: www.sleepcycle.com/

[17] C. M. Inc, "Fastest co2 sensor in the world measures co2 in breath 20 times a second," April 2013. [Online]. Available: http://www.co2meter.com/blogs/news/7721367-fastest-co2-sensor-in-the-world-measures-co2-in-breath-20-times-a-second

[18] iHealthlabs, "Wireless blood pressure wrist monitor," April 2014. [Online]. Available: www.ihealtlabs.com/

[19] S. Rhee, B.-H. Yang, K. Chang, and H. Asada, "The ring sensor: a new ambulatory wearable sensor for twenty-four hour patient monitoring," vol. vol.4, Piscataway, NJ, USA, 1998//, pp. 1906 – 9, finger ring sensor;patient monitoring;ambulatory wearable sensor;photodetectors;LEDs;pulse oximetry;blood oxygen saturation monitoring;digital wireless communication link;sensor hardware;sensor software;motion artifact;ambient light;telemetered device;photoplethysmograms;sample-and-hold circuit;signal conditioner;microprocessor;blood flow monitoring;. [Online]. Available: http://dx.doi.org/10.1109/IEMBS.1998.746970

[20] Neumitra, "Measure and manage brain health and performance," April 2014. [Online]. Available: neumitra.com/

[21] Diabetes.co.uk, "Insulin pumps," April 2014. [Online]. Available: www.diabetes.co.uk/

[22] Y. Rahmat-Samii and H. Rajagopalan, "Medical monitoring and diagnostics using ingestible capsule antennas: An exciting paradigm in biotelemetry," in *Wireless Information Technology and Systems (ICWITS), 2010 IEEE International Conference on*, Aug 2010, pp. 1–1.

[23] J. Klonovs, C. Petersen, H. Olesen, and A. Hammershoj, “Id proof on the go: Development of a mobile eeg-based biometric authentication system,” *Vehicular Technology Magazine, IEEE*, vol. 8, no. 1, pp. 81–89, March 2013.

[24] W. Li, C. Jaramillo, and Y. Li, “Development of mind control system for humanoid robot through a brain computer interface,” in *Intelligent System Design and Engineering Application (ISDEA), 2012 Second International Conference on*, Jan 2012, pp. 679–682.

[25] M. Teplan, “Fundamentals of eeg measurement,” *Measurement Science Review*, vol. 2, 2002.