Sleep Monitoring and Sleep Apnea Event Detection using a 3D camera

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Abstract— This non-invasive method detects the stages of sleep from the respiratory motion recorded with a 3D time-of-flight (TOF) camera. After the patient falls asleep, his/her muscles relax and the degree of relaxation is different in each sleep stage. The relaxation of abdominal muscles leads to slight variations in the movement of the abdomen in some regions. From 3D video recordings, the signal of respiratory movement is extracted from all visible regions. The characteristic features of different sleep stages are extracted, comparing the correlation (coefficients) between different signals. In a similar way, obstructive sleep apnea events are also detected.

Keywords- sleep stages, apnea, sleep monitor

I. INTRODUCTION

Sleep is studied and analysed using a system called polysomnography (PSG). It is mainly used to record the sleep of a person, to diagnose sleep disorders and to investigate differences between normal and abnormal sleep. The PSG recordings are performed in a sleep laboratory. The equipment used for monitoring sleep by PSG is composed of: an electroencephalograph (EEG) used to record brainwave activity, an electrooculograph (EOG) for recording the activity of the eyes, an electromyograph (EMG) for recording activity in muscles and other equipment used to collect signals related to breathing (respiration) and to record the airflow through the nose and mouth.

During the different stages of sleep, the muscles become more and more relaxed and, during the rapid eye movement (REM) stage, muscle tone is weakest. REM sleep is distinct from non-REM sleep because in this stage, the EEG is similar to the stage of waking, but in this stage the body looks like paralysed. REM sleep is also characterized by the typical rapid eye movements that are recorded by the EOG.

The respiratory motion recorded with Time-of-Flight (ToF) [1] cameras has been proposed for a respiratory gating system applied to radiotherapy [2] and for various other 3D devices proposed for diagnosis and screening of sleep respiratory disturbance [3–7].

II. SLEEP FEATURE

The recorded 3D image is divided into twelve zones as in Fig. 2 and the average distance to each zone is obtained from the distance image. The recorded signals are the variation in time of the mean distance to the selected zones \( D_{ij}(t) \) (Fig. 3).

\[ D_{ij}(t) = \frac{D_{F_{ij}}(t) - D_{F_{ij}}^m(t)}{D_{F_{ij}}^m(t)} \]

To establish the waking and sleep stages from Fig. 2, we must set a threshold value which differentiates between these

![Image](image-url)

Figure 1. The distance image of the patient’s body is divided into twelve zones; zone [1, 1] is darker in the image.
stages, but this may vary for different patients. The respiratory effort is controlled by the physiological needs of the body, and mainly by the “oxygen level” in the blood, and so it is not a constant. This effort shows significant fluctuations, which increase during OSA events and these fluctuations increase the uncertainty in correctly identifying the sleeping period from Eq. (1).

The graph in Fig. 2 shows clearly that there is a relation between the ratio of intercostals and diaphragm muscle effort and the waking and sleep stages. The sleeping period of the patient cannot be precisely evaluated using the Eq. (1) and a threshold level because this level may be influenced by other physiological factors and can vary from person to person. From Fig. 2, the sleeping period changes by about 20% if this level is moved from 1 to 1.5.

Figure 2. Time variation of signal (1) as solid line and threshold value = 1 as dotted line. The time in [s] is represented on the abscissa and the values of Eq. 1 are shown on the ordinate.

The analysis of all $D_f(t)$ signals reveals an interesting feature between signals $D_{f_{2,2}}(t)$ and $D_{f_{4,2}}(t)$; these two signals from the abdomen region must be similar, the single difference is that the second is closer to the border of the abdomen. From Fig. 2, the patient falls asleep 300–400 s after starting the recording, but it is difficult to establish a precise moment. In Fig. 3, the time variation of these two signals is represented in the time interval [200s, 400s], and we observe that the signal $D_{f_{4,2}}(t)$ becomes visibly distorted after time 250 s.

Figure 3. The amplitude of the distance measured to the two abdomen regions in mm is represented on the ordinate. The time in [s] is represented on the abscissa. The first signal was shifted by +2 mm and the second by -2 mm.

Using the samples acquired during a period $T = 4$ s, we compute the correlation coefficient $C_{3,2}^{2}$ and $C_{4,2}^{2}$ between the signals $D_{f_{2,2}}$ and $D_{f_{3,2}}(t)$ on one hand and between $D_{f_{3,2}}(t)$ and $D_{f_{4,2}}(t)$ on the other hand:

$$C_{3,2}^{2} = \sum_{i=0}^{n} D_{f_{2,2}}(t_i) \cdot D_{f_{3,2}}(t_i)$$
$$C_{4,2}^{2} = \sum_{i=0}^{n} D_{f_{3,2}}(t_i) \cdot D_{f_{4,2}}(t_i)$$

Figure 4. Time variation of the correlation coefficients. The time in [s] is represented on the ordinate.

The time variation of these two correlation coefficients is plotted in Fig. 4 in blue and red, respectively. Correlation coefficient $C_{4,2}^{2}$ changes significantly around time $t = 300$ s when the patient falls asleep. The other curve has a low increase and after time $t = 300$ s has a steady evolution in contrast with the other curve which changes significantly. Different sleep stages strongly affect correlation coefficient $C_{4,2}^{2}$ up to REM sleep when it has the same behaviour as in the waking stage. In the REM sleep stage, the correlation coefficient $C_{4,2}^{2}$ has important variations caused by OSA events, and these events can be easily detected in this way.

Suppose that signals $D_{f_{3,2}}(t)$ and $D_{f_{4,2}}(t)$ result from a linear combination of two distinct imaginary signals, one representing only the respiratory motion $P(t)$ and the other related to all the other physiological activities that include the sleep $P(t)$, then we try to separate these two signals. Probably, these signals are not totally uncorrelated or independent but, in any case, they are much less correlated than the signals $D_{f_{3,2}}(t)$ and $D_{f_{4,2}}(t)$, and we suppose that a good approximation of $P(t)$ and $P(t)$ is obtained by using principal component analysis (PCA) or independent component analysis (ICA) methods.

The signals $D_{f_{3,2}}(t)$ and $D_{f_{4,2}}(t)$ are decomposed into independent and principal components, and we retain only the second component $P(t)$ that represents the physiological events related to sleep. The decomposition was performed mainly to eliminate (separate) the respiratory motion. In Fig. 5, the RMS values alone are represented by the second independent and principal components (the $P(t)$ components). The independent component is plotted in blue and the principal component in dotted red. These two plots clearly represent the transition to different sleep stages.
The decomposition into independent components has been performed by an original method. The covariance of two random variables $U$ and $V$ is zero when these variables are independent or orthogonal. If $U$ is a linear combination of two independent normalized random variables $x$ and $y$, $U = a \cdot x + b \cdot y$ then an orthogonal random variable of $U$ is $V = b \cdot x - a \cdot y$, and these variable must satisfy Eq. (3).

$$\text{var}(U + V) - \text{var}(U - V) = 0$$  (3)

A similar equation to (3) is obtained by replacing the variance operator with the mean absolute deviation (4). This new equation is satisfied if the random variables $U$ and $V$ are independent or orthogonal, but the orthogonal random variable $V'$ of $U$ is different from $V$. In this case, random variables $U$ and $V$, which satisfy both Eq. (3) and (5) are independent (or almost).

$$\phi(x) - E[|X - E[X]|]$$  (4)

$$\phi(U + V') - \phi(U - V') = 0$$  (5)

If $X$ and $Y$ can be decomposed into two independent components $U$ and $V$ (6) then these must satisfy Eqs. (3) and (5). Because we have only two equations and four unknowns the decomposition can be realized up to two multiplicative constants $b_1, a_2$ (7) and the independent components are represented by the simpler Eq. (8).

$$U = a_1 \cdot X + b_1 \cdot Y, \quad V = a_1 \cdot X + b_1 \cdot Y$$  (6)

$$U = b_1 \cdot (a_1 \cdot X + Y), \quad V = a_1 \cdot (X + b_1 \cdot Y)$$  (7)

$$U = a_1 \cdot X + Y, \quad V = X + b_1 \cdot Y$$  (8)

The independent components are found by minimizing relation (9). The problem has solutions only if at least one independent component is non-Gaussian.

$$|\text{var}(U + V) - \text{var}(U - V)| + |\phi(U + V') - \phi(U - V')|$$  (9)

The ICA method was tested with two orthogonal random variables $X$ and $Y$ as in Eq. (10), where $x_1$ and $y_2$ are two computer-generated pseudo random variables with normal ($x_1$) and uniform ($y_2$) distributions. Parameter $a$ was varied from one to ten and in each case the decomposition was better than 99%.

$$X = a \cdot \frac{x_1}{\sigma(x_1)} + \frac{y_2}{\sigma(y_2)}, \quad Y = \frac{x_1}{\sigma(x_1)} - a \cdot \frac{y_2}{\sigma(y_2)}$$  (10)

The results obtained by this method depend on the distribution function of $X$ and $Y$. There are situations when $X$ and $Y$ are orthogonal and both relations (3) and (5) are fulfilled as in the case when both variables are Gaussian. More orthogonality conditions like Eq. (3) can be obtained by using a generalized mean deviation (11) (GMD) similar to the standard deviation. The absolute deviation is the particular case when $p = 1$ and the standard deviation relation is for $p = 2$.

$$\sigma_p(X) = \left(E[|X - E[X]|^p] \right)^{\frac{1}{p}}, \quad p \in \mathbb{R}^+$$  (11)

Two random variables $X$ and $Y$ are independent or orthogonal for the pseudo measure $\sigma_p$ if Eq. (12) is verified.

$$\sigma_p(X + Y) - \sigma_p(X - Y) = 0$$  (12)

The algorithm for decomposition into independent components may quickly converge if instead of Eq. (9) the equivalent relation (13) that gives the possibility of choosing between different values of $p$ and $q$ is used. In Fig. 6, the value of the left-hand side of Eq. (12) is shown as a function of $p$ for two different couples $X$ and $Y$. This graph shows that if $X$ and $Y$ can be decomposed into independent components, then it has important variations, otherwise it follows a horizontal straight line. For the first couple, the decomposition is possible and we can choose, for example, $p_1 = 1$ and $p_2 = 2$. The decomposition of the second couple into independent components may be possible if we use $p_1 = 3$ and $p_2 = 4$.

$$|\sigma_p(U + V) - \sigma_p(U - V)| + |\sigma_p(U + V') - \sigma_p(U - V')|$$  (13)

The results have been compared to the PSG recordings validated by a specialist doctor, and we obtained a good correlation. According to this method, a definite transition between the states of being awake and being asleep was observed. From the EEG recordings, this transition is placed in the first stage of sleep close to the beginning of the second stage. The clear transition, occurred around $t = 300$ s in Figs. 4 and 5 and represents the moment when the patient’s respiration motion is controlled only by the central nervous system. Transitions to other sleep stages are also represented by clear changes in respiratory motion. The respiratory motion in REM sleep stage is quite similar to the awakening stage.
What is important is that we can extract from the respiratory motion a feature which marks the difference between waking and sleeping stages. This feature is obtained only from the ToF camera distance images without any wire connected to the body.

III. OBSTRUCTIVE SLEEP APNEA FEATURES.

Obstructive sleep apnea events are detected by analysing the respiratory muscle effort [8–10]. During an obstructive sleep apnea event, when the airways are obstructed, the respiratory effort will produce an antiphase movement of the thorax and abdomen. When the thorax is compressed, the inside air will expand the abdomen and vice versa. To reveal these antiphase movements, we compare the motion recorded in a zone in the upper part of the chest with one in the abdomen region. In Fig. 7 the movements of the chest are represented by a solid line and of those of the abdomen by a dotted grey line.

The OSA events can be detected from the correlation coefficient between the chest and abdomen regions. The value of this coefficient is positive in the case of normal breathing and becomes negative during an OSA event. In Fig. 8, the binary signal computed with Eq. 14 is represented graphically.

\[
osa_x = \text{sign} \left[ \text{corr}(D_{[1,2]}, D_{[2,2]}) \right]
\]

\[
osa_z = -\text{sign} \left[ \text{corr}(D_{[3,2]}, D_{[2,2]}) \right]
\]

Figure 7. Time variation of filtered distances to chest zone [1, 2], solid line, and to abdomen zone [3,2], dotted line. On the abscissa the time in [s] is represented and on the ordinate the motion amplitude in [mm].

Figure 8. The binary signal plotted with a dotted blue line is on when the patient is sleeping. Time variation of OSA binary signal is plotted as a solid red line. On the abscissa the time in [s] is represented and on the ordinate the value of the binary digital signals.

IV. CONCLUSION

The sleep monitor based on a 3D camera is a non-invasive diagnosis method. The most important result is the feature that establishes the waking to sleeping transition. Up to now, the different sleep stages have been detected using an electroencephalogram and this procedure has been developed during half a century [11]. These first results demonstrate the possibility of detecting different sleep stages from respiratory motion.

The method for observing the transitions to different sleep stages or measuring the sleeping period by Eq. 2 can be implemented in PSG using belts instead of TOF camera. Belts with accelerometer sensors are generally used in PSG for monitoring the respiratory effort of the chest and abdomen. The signals from these sensors can be processed according to our method to obtain similar results to the video recordings.

Comparing the electroencephalogram validated by a specialist medic with our recordings, the “sleep” signal is on during sleep stages 2 and 4. During REM sleep, the mean value of the “sleep” signal is the same as in the wakefulness stage but with more irregularities.

Many people wish to know how they sleep and if they have a sleep disorder. This 3D camera in mass production will be cheap and affordable for everyone. The OSA event detection algorithm is simple and can be implemented easily. This can be improved by tracking the patient movements during sleep. This method can also be used for screening of sleep respiratory disturbances.

The ICA method is simple, gives good results and can easily be used in many other applications.

REFERENCES