2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Automatic 3D Video Analysis of Upper and Lower Body Movements to Identify Isolated REM Sleep Behavior Disorder: A Pilot Study*

Matteo Cesari, Bernhard Kohn, Evi Holzknecht, Abubaker Ibrahim, Anna Heidbreder, Melanie Bergmann, Elisabeth Brandauer, Birgit Högl, Heinrich Garn and Ambra Stefani

Abstract — **Rapid eye movement (REM) sleep behavior disorder (RBD) is a parasomnia characterized by dream enactment, abnormal jerks and movements during REM sleep. Isolated RBD (iRBD) is recognized as the early stage of alpha-synucleinopathies, i.e. dementia with Lewy bodies, Parkinson's disease and multiple system atrophy. The certain diagnosis of iRBD requires video-polysomnography, evaluated by experts with time-consuming visual analyses. In this study, we propose automatic analysis of movements detected with 3D contactless video as a promising technology to assist sleep experts in the identification of patients with iRBD. By using automatically detected upper and lower body movements occurring during REM sleep with a duration between 4s and 5s, we could discriminate 20 iRBD patients from 24 patients with sleep-disordered breathing with an accuracy of 0.91 and F1-score of 0.90. This pilot study shows that 3D contactless video can be successfully used as a non-invasive technology to assist clinicians in identifying abnormal movements during REM sleep, and therefore to recognize patients with iRBD. Future investigations in larger cohorts are needed to validate the proposed technology and methodology.**

I. Introduction

Rapid eye movement (REM) sleep behavior disorder (RBD) is a parasomnia characterized by dream enactment and abnormal muscular activity during REM sleep [1]. Its isolated form (iRBD) is considered an early stage alpha-synuclein related neurodegeneration (i.e. Parkinson's disease, dementia with Lewy bodies and multiple system atrophy) [2].

Currently, RBD is diagnosed in specialized sleep centers with video-polysomnography (v-PSG), which consists of the simultaneous recording of electrophysiological signals (electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), electrocardiogram and respiratory signals) and 2D infrared video over night [3]. Diagnosis of RBD requires v-PSG demonstration or a clinical history of dream-enacting behaviors and v-PSG demonstration of abnormal muscular activity in REM sleep (REM sleep without atonia (RWA)) [1]. The current guidelines call for quantification of muscular activity during REM sleep [3]. Manual RWA quantification is time consuming and prone to inter-rater variability [4]. Because of this, some groups have proposed automated methods to quantify RWA [5]–[12].

The methods quantifying RWA (manual and automatic) provide information on muscular activity during REM sleep on few selected muscles, but they do not provide any information concerning abnormal jerks and movements during REM sleep occurring in different body areas. Such movements are currently analyzed with visual time-consuming video analyses [13]. There is therefore a need for methods that can automatically identify movements during REM sleep to help clinicians making more precise and fast diagnoses.

Previous studies have proposed automatic analysis of infrared 2D videos recorded during v-PSG [14]. However, these studies included only healthy subjects who were not allowed to use a blanket. Recent studies have instead shown that automatic analysis of 3D videos is more useful to monitor and quantify movements during sleep. Such technology has been proven useful to detect sleep apneas [15] and periodic limb movements during sleep [16]. Recently, we applied this technology to identify iRBD patients by analysis of automatically detected leg movements [17]. Minor leg jerks with a duration between 0.1 s and 2 s discriminated iRBD patients from patients with other sleep disorders with 97.5% sensitivity and 85.9% specificity [17].

Previous investigations showed that movements and jerks in the upper body during REM sleep are a specific hallmark of RBD [18]. Furthermore, muscular activity recorded in the upper extremities is more specific than muscular activity in the lower extremities to detect patients with RBD [19], [20].

Based on this evidence, the aim of this pilot study was to understand whether REM sleep movements detected in the upper body with automatic 3D video analysis allow improved and more specific automatic identification of iRBD patients.

II. Methods

A. Participants and v-PSG recordings

We included 20 iRBD patients and 24 patients with untreated sleep-disordered breathing (SDB). The patients underwent one night v-PSG at the Sleep Disorder Unit of the Department of Neurology, Medical University Innsbruck, Austria. Diagnoses were made according to international criteria [1]. V-PSGs were performed according to the American Academy of Sleep Medicine recommendations and consisted of simultaneous recording of EOG, EEG, EMG (mentalis, submentalis, bilateral tibialis anterior and bilateral flexor digitorum superficialis muscles, according to the Sleep Innsbruck Barcelona – SINBAR – recommendations [19]), electrocardiogram, respiratory signals and infrared 2D videos. Expert technicians manually scored sleep stages and respiratory events. From the scored respiratory events, the apnea-hypopnea index (AHI) was computed. Periodic leg movements were automatically scored with a validated

*Research supported by the Austrian Science Fund (project KLI 677-B31)

M. Cesari, E. Holzknecht, A. Ibrahim, A. Heidbreder, M. Bergmann, E. Brandauer, B. Högl and A. Stefani are with the Department of Neurology, Medical University Innsbruck, Anichstrasse. 35, 6020 Innsbruck, Austria. (Corresponding author: Matteo Cesari, e-mail: matteo.cesari@i-med.ac.at, phone: +43 512 504 80848).

B. Kohn and H. Garn are with the Competence Unit Sensing and Vision Solutions, AIT Austrian Institute of Technology GmbH, Giefinggasse 4, 1210 Vienna, Austria.

software [21] and the periodic limb movement index (PLMS index) was computed. RWA was quantified with a semi-automated validated software according to the SINBAR recommendations [9]. The demographic and sleep information of the patients included in the study are shown in Table I. This study was approved by the ethical committee of the Medical University Innsbruck, Austria. Patients provided written informed consent prior to inclusion in the study.

B. 3D video recording

3D videos were recorded simultaneously to the v-PSGs with a Microsoft Kinect One sensor (Microsoft Corporation) mounted on the ceiling above the bed. The technology is based on a time-of-flight sensor, measuring the distance between the camera and a surface by determining the time needed for infrared light, emitted by the camera, to return to the camera after being reflected by the surface of an object. Depth images (i.e. images giving information on the distance values of the objects from the camera, Fig. 1a) had a resolution of 512x424 pixels and were recorded at a rate of 30 frames per second.

C. Movement detection

To detect movements, raw depth images were first resampled with a 4x4 kernel. For each pixel (i, j) and for each frame t, the motion signal $m_{i,j}(t)$ was obtained via convolution over time. A detailed description can be found elsewhere [22]. By combining the motion signal of each pixel, it was possible to generate motion maps for each frame (Fig. 1b). Three regions of interest (ROIs) were manually selected for each patient: lower body (red rectangle in Fig. 1b), upper body (purple rectangle in Fig. 1b) and upper+lower body (consisting of both the lower and upper body ROIs). For each ROI and for each frame t, the movement strength $S(t)$ was calculated as the sum of all the values $m_{i,j}(t)$ included in the ROI. Based on the signal $S(t)$, movements were identified by using two thresholds, as previously described [22].

For the upper body ROI, respiratory effort was identified with the method described in [23]. Movements caused by respiration effort were excluded from analysis.

The head was excluded from the upper body ROI, as it was observed that the head region could not reflect light with high intensity and that its complex surface was causing false movement detection. Furthermore, neither the upper nor the lower body ROIs included the hips area, as movements in this area could not be attributed to only one of the two ROIs.

D. 3D movement feature extraction

The automatically identified movements were grouped according to their duration. In particular, the following duration ranges were defined: [0.1s, 2s), [2s, 3s), [3s, 4s), [4s, 5s), …, [14s, 15s). For each subject, ROI, and duration range, the following two 3D movement features were calculated: 3D rate (the number of movements in REM sleep per hour of REM sleep) and 3D ratio (the total movement duration time in seconds in REM sleep divided by the total REM sleep time in seconds). The 3D ratio feature was multiplied by the scaling factor 3600. This scaling factor value was chosen in order to have both 3D features with the same order of magnitude. To compute these 3D features, the manually scored REM sleep was used. The different duration ranges were selected to assess whether short jerks or longer movements in the different ROIs could best differentiate iRBD from SDB patients.

TABLE I. DEMOGRAPHIC AND SLEEP INFORMATION. VALUES ARE SHOWN AS MEDIAN AND 25TH-75TH PERCENTILES. SIGNIFICANT P-VALUES ARE HIGHLIGHTED IN BOLD.

Parameter	iRBD	SDB	p-value
Males/females[a]	17/3	17/6	0.176
Age[b]	67 [58-73]	61 [52-68]	0.092
REM duration (min)[b]	73.0 [44.0-83.0]	74.0 [47.0-89.0]	0.733
AHI (h^{-1})[b]	7.9 [4.4-13.8]	26.8 [12.0-48.6]	**<0.001**
PLMS (h^{-1})[b]	29.1 [19.4-72.5]	16.1 [6.1-29.7]	**0.007**
RWA (%)[b]	66.3 [53.7-77.6]	21.2 [13.3-28.4]	**<0.001**

a: Fisher exact test; b: Mann-Whitney U test

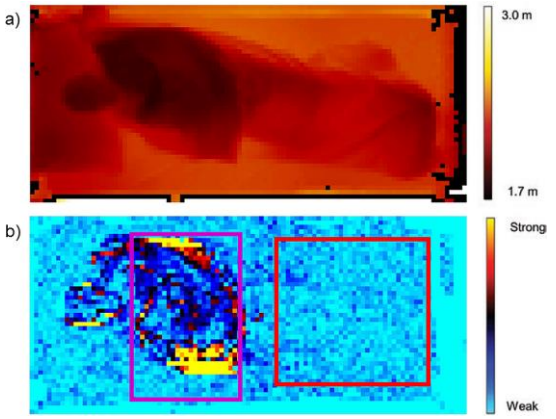

Figure 1. a) Depth image showing the distance between the camera and the sleeping subject. b) Motion map obtained for one frame showing the intensity of the motion signal for each pixel. The purple rectangle shows the upper body region of interest (ROI) and the red rectangle the lower body ROI.

E. Discrimination of iRBD patients

For each 3D feature, range of movement duration and ROI, a receiver operating characteristic (ROC) curve to distinguish iRBD (positive class) from SDB (negative class) was obtained. For each ROC curve, the optimal threshold was identified as the one maximizing Youden index [24]. Using this threshold, the number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) were obtained and used to compute accuracy ((TP+TN)/(TP+TN+FP+FN)), sensitivity (TP/(TP+FN)), specificity (TN/(TN+FP)) and F1-score ((2TP)/(2TP+FP+FN)) as performance measures of the discrimination of iRBD from SDB patients. For each ROI, we identified the duration range for which the highest accuracy in the discrimination was achieved.

F. Correlation of features and RWA

RWA is the electrophysiological hallmark of RBD and is required to make a diagnosis of RBD [1]. To understand the relationship between the obtained 3D features and RWA, we calculated the Spearman correlation coefficient and its significance between RWA values and the movement features that could best discriminate iRBD from SDB patients.

III. RESULTS

For the lower body ROI, the highest accuracy values were achieved for the 3D features extracted from movements with duration between 0.1s and 2s. For the upper and upper+lower body ROIs, the highest accuracy was achieved when considering 3D features extracted from movements with duration in the range [4s, 5s). Table II reports the

TABLE II. DISCRIMINATION PERFORMANCES OF 3D FEATURES OBTAINED IN THE DIFFERENT REGIONS OF INTEREST.

ROI	Duration	Feature	Accuracy [-]	F1-score [-]	Sensitivity [-]	Specificity [-]
Lower body	[0.1s-2s)	3D rate	0.86	0.86	0.90	0.83
	[0.1s-2s)	3D ratio	0.89	0.88	0.90	0.88
Upper body	[4s-5s)	3D rate	0.89	0.88	0.90	0.88
	[4s-5s)	3D ratio	0.89	0.88	0.90	0.88
Upper+lower body	[4s-5s)	3D rate	0.91	0.90	0.90	0.92
	[4s-5s)	3D ratio	0.91	0.90	0.90	0.92

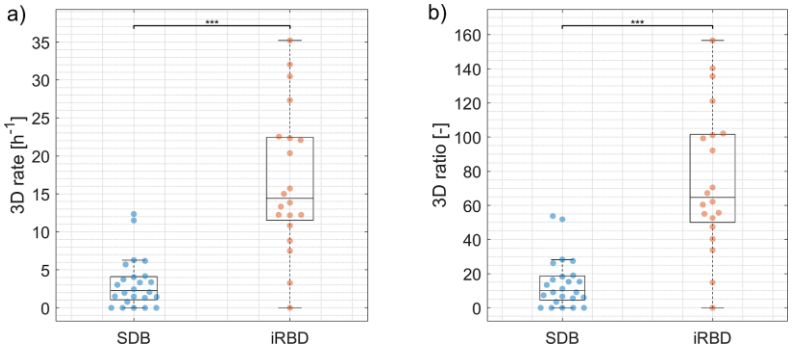

Figure 2. Distributions of the features a) 3D rate and b) 3D ratio of the automatically detected movements with duration [4s-5s) in the upper+lower body region of interest. ***: p-value <0.001 (obtained with Mann-Whitney U tests) SDB: patients with sleep-disordered breathing; iRBD: patients with isolated REM sleep behavior disorder.

TABLE III. SPEARMAN CORRELATION COEFFICIENTS (ρ) BETWEEN THE 3D FEATURES AND RWA. SIGNIFICANT P-VALUES ARE HIGHLIGHTED IN BOLD.

Region of interest	Duration	Feature	ρ	p-value
Lower body	[0.1s-2s)	3D rate	0.698	**<0.001**
	[0.1s-2s)	3D ratio	0.704	**<0.001**
Upper body	[4s-5s)	3D rate	0.717	**<0.001**
	[4s-5s)	3D ratio	0.714	**<0.001**
Upper+lower body	[4s-5s)	3D rate	0.744	**<0.001**
	[4s-5s)	3D ratio	0.749	**<0.001**

discrimination performances achieved for these optimal duration ranges. When comparing the ROIs, the 3D rate and 3D ratio of movements with duration [4s, 5s) in the upper+lower body ROI achieved the highest accuracy, F1-score and specificity in the discrimination of patients with iRBD from patients with SDB. Their distribution is shown in Fig. 2. Table III shows the Spearman correlation coefficients between the 3D features and RWA. The highest correlation coefficients were obtained for the 3D rate and 3D ratio of movements in the upper+lower body with a duration between 4s and 5s.

IV. DISCUSSION

In this pilot study, we showed that features extracted from upper and lower body movements with duration between 4s and 5s automatically detected with 3D contactless video during REM sleep can discriminate patients with iRBD from patients with SDB. Furthermore, our results show that integration of movements from lower and upper body increases specificity for identification of patients with iRBD. Therefore, the results show that 3D video technology analyzing upper and lower body movements can help clinicians in diagnosing RBD.

Patients with SDB were included with the rationale that sleep-related breathing disorders are very common in the general population aged 50 or more [25] and that sleep-related breathing disorders are a differential diagnosis of RBD, as movements can occur at the end of apneic events [26].

When considering only movements in the lower body ROI, the results of this study confirm previous reports [17], showing that short leg jerks with duration <2s could identify patients with iRBD. When considering the upper and upper+lower body, 3D features extracted from movements with duration [0.1s, 2s) could not discriminate patients with iRBD from patients with SDB (the accuracy was lower than 0.70). This is likely because some respiration-related movements could not be recognized with the strategy implemented to identify respiratory effort. As visual video-analyses have shown that short jerks in the upper extremities are frequent in patients with iRBD [18], future studies should investigate how to employ 3D video to better distinguish short jerks characteristic of RBD from respiration-related movements.

Features extracted from upper and upper+lower body movements with duration in the range [4s, 5s) could discriminate iRBD from SDB patients. It can be hypothesized that movements with this duration are likely related to longer movements characteristic of iRBD patients. In the future, the movements automatically identified by 3D video analysis should be visually analyzed by clinicians to understand whether they correspond to typical RBD movements e.g. punching, kicking.

Movements with duration longer than 5s in the lower, upper, and upper+lower body ROIs could not distinguish iRBD from SDB patients. This is likely because movements longer than 5s might be related to arousals, and arousal frequency has been shown not to be significantly different between RBD and the general population [27].

Movements from the upper+lower body with duration between 4s and 5s showed higher performances in the identification of iRBD patients, compared to when only lower body jerks were considered. In particular, upper+lower body movements with duration [4s, 5s) were more specific for

identifying RBD patients than lower body short jerks, in line with previous investigations of muscular activity in RBD [19], [20]. Furthermore, the correlation analyses show that upper and whole-body movements with duration in the range [4s, 5s) were more correlated to RWA than lower body jerks. This confirms the reliability of the automatically detected whole-body movements as a measure of abnormal activity during REM sleep. In short, the analyses here presented show that movements form the upper+lower body are more accurate to identify iRBD patients compared to only short leg jerks.

In the future, the technology and methodology here employed should be evaluated in larger cohorts, including healthy controls and patients with other sleep disorders associated with movements (e.g. restless legs syndrome). Furthermore, future studies should compare the accuracy of the proposed technology for the identification of iRBD patients to alternative technologies (e.g. actigraphy). Improvements on the accuracy of 3D video could be achieved by combining jerks in the lower limbs with longer movements in the upper body with machine learning models. In this study, the ROIs were selected manually, which is a time-consuming task. Automatic selection of ROIs should be investigated in the future. At the current stage, the proposed 3D video-technology requires information from v-PSG to identify periods of REM sleep and therefore might be used in sleep clinics as a supportive diagnostic tool. In the perspective of making such technology as stand-alone to identify and monitor RBD patients in home environments, a number of investigations are necessary. First, it has to be analyzed whether movements recorded for the whole night (therefore not distinguishing sleep stages) can be analyzed to identify patterns of movements typical of REM sleep and subsequently identify patients with RBD. Second, the sensor used in this study is suitable for sleep laboratories but is not practical to be installed in home environments. Future investigations should be performed to evaluate whether smaller and portable 3D video technologies can be used to identify RBD patients.

V. Conclusions

We showed that iRBD patients can be discriminated from SDB patients using contactless 3D video automatic detection of upper and lower body movements during REM sleep with duration between 4s and 5s. The results indicate that contactless 3D video is a promising technology to support clinicians in recognizing patients with iRBD.

Acknowledgments

We thank Heinz Hackner for the manual v-PSG scoring.

References

[1] American Academy of Sleep Medicine, *The international classification of sleep disorders (ICSD-3)*, 3rd ed. Darien, IL, 2014.

[2] B. Högl, A. Stefani, and A. Videnovic, "Idiopathic REM sleep behaviour disorder and neurodegeneration - An update," *Nat. Rev. Neurol.*, vol. 14, no. 1, pp. 40–55, 2018, doi: 10.1038/nrneurol.2017.157.

[3] R. B. Berry *et al.*, *The AASM manual for the scoring of sleep and associated events: rules, terminology and technical specifications: version 2.6*. Darien, IL: American Academy of Sleep Medicine, 2020.

[4] D. L. Bliwise *et al.*, "Inter-rater agreement for visual discrimination of phasic and tonic electromyographic activity in sleep," *Sleep*, vol. 41, no. 7, p. zsy080, 2018, doi: 10.1093/sleep/zsy080.

[5] R. Ferri *et al.*, "Improved computation of the atonia index in normal controls and patients with REM sleep behavior disorder," *Sleep Med.*, vol. 11, pp. 947–49, 2010, doi: 10.1016/j.sleep.2010.06.003.

[6] J. W. Burns, F. B. Consens, R. J. Little, K. J. Angell, S. Gilman, and R. D. Chervin, "EMG variance during polysomnography as an assessment for REM sleep behavior disorder," *Sleep*, vol. 30, no. 12, pp. 1771–78, 2007, doi: 10.1093/sleep/30.12.1771.

[7] J. Kempfner, G. L. Sorensen, M. Nikolic, R. Frandsen, H. B. D. Sorensen, and P. Jennum, "Rapid Eye Movement Sleep Behavior Disorder as an Outlier Detection Problem," *J Clin Neurophysiol*, vol. 31, pp. 86–93, 2014.

[8] R. Frandsen, M. Nikolic, M. Zoetmulder, L. Kempfner, and P. Jennum, "Analysis of automated quantification of motor activity in REM sleep behaviour disorder," *J. Sleep Res.*, vol. 24, no. 5, pp. 583–90, 2015, doi: 10.1111/jsr.12304.

[9] B. Frauscher *et al.*, "Validation of an Integrated Software for the Detection of Rapid Eye Movement Sleep Behavior Disorder," *Sleep*, vol. 37, no. 10, pp. 1663–71, 2014, doi: 10.5665/sleep.4076.

[10] M. Cesari *et al.*, "Validation of a new data-driven automated algorithm for muscular activity detection in REM sleep behavior disorder," *J. Neurosci. Methods*, vol. 312, pp. 53–64, 2019, doi: 10.1016/j.jneumeth.2018.11.016.

[11] G. Mayer *et al.*, "Quantification of Tonic and Phasic Muscle Activity in REM Sleep Behavior Disorder," *J. Clin. Neurophysiol.*, vol. 25, no. 1, pp. 48–55, Feb. 2008, doi: 10.1097/WNP.0b013e318162acd7.

[12] M. Cesari *et al.*, "Comparison of computerized methods for rapid eye movement sleep without atonia detection.," *Sleep*, vol. 41, no. 10, p. zsy133, Oct. 2018, doi: 10.1093/sleep/zsy133.

[13] A. Stefani, J. Santamaria, A. Iranzo, H. Hackner, C. H. Schenck, and B. Högl, "Nelotanserin as symptomatic treatment for rapid eye movement sleep behavior disorder: a double-blind randomized study using video analysis in patients with dementia with Lewy bodies or Parkinson's disease dementia," *Sleep Med.*, vol. 81, pp. 180–187, May 2021, doi: 10.1016/j.sleep.2021.02.038.

[14] M. Scatena *et al.*, "An integrated video-analysis software system designed for movement detection and sleep analysis. Validation of a tool for the behavioural study of sleep," *Clin. Neurophysiol.*, vol. 123, no. 2, pp. 318–323, Feb. 2012, doi: 10.1016/J.CLINPH.2011.07.026.

[15] H. Garn *et al.*, "3D detection of the central sleep apnoea syndrome," *Curr. Dir. Biomed. Eng.*, vol. 3, no. 2, pp. 829–833, 2017, doi: 10.1515/cdbme-2017-0174.

[16] S. Seidel *et al.*, "Contactless detection of periodic leg movements during sleep: A 3D video pilot study," *J. Sleep Res.*, 2020.

[17] M. Waser *et al.*, "Automated 3D video analysis of lower limb movements during REM sleep: a new diagnostic tool for isolated REM sleep behavior disorder," *Sleep*, vol. 43, no. 11, p. zsaa100, 2020, doi: 10.1093/sleep/zsaa100.

[18] B. Frauscher *et al.*, "Video analysis of motor events in REM sleep behavior disorder," *Mov. Disord.*, vol. 22, no. 10, pp. 1464–1470, 2007, doi: 10.1002/mds.21561.

[19] B. Frauscher *et al.*, "Normative EMG Values during REM Sleep for the Diagnosis of REM Sleep Behavior Disorder," *Sleep*, vol. 35, no. 6, pp. 835–47, 2012, doi: 10.5665/sleep.1886.

[20] A. Iranzo *et al.*, "Usefulness of the SINBAR electromyographic montage to detect the motor and vocal manifestations occurring in REM sleep behavior disorder," *Sleep Med.*, vol. 12, no. 3, pp. 284–288, Mar. 2011, doi: 10.1016/j.sleep.2010.04.021.

[21] A. Stefani, A. Heidbreder, H. Hackner, and B. Högl, "Validation of a leg movements count and periodic leg movements analysis in a custom polysomnography system," *BMC Neurol.*, vol. 17, no. 1, p. 42, 2017, doi: 10.1186/s12883-017-0821-6.

[22] M. Gall *et al.*, "Automated Detection of Movements During Sleep Using a 3D Time-of-Flight Camera: Design and Experimental Evaluation," *IEEE Access*, 2020.

[23] H. Garn *et al.*, "Contactless 3d detection of respiratory effort," in *IFMBE Proceedings*, 2017, vol. 65, pp. 418–421, doi: 10.1007/978-981-10-5122-7_105.

[24] W. J. Youden, "Index for rating diagnostic tests," *Cancer*, vol. 3, no. 1, pp. 32–35, 1950, doi: 10.1002/1097-0142(1950)3:1<32::AID-CNCR2820030106>3.0.CO;2-3.

[25] R. Heinzer *et al.*, "Prevalence of sleep-disordered breathing in the general population: THE HypnoLaus study," *Lancet Respir. Med.*, vol. 3, no. 4, pp. 310–318, Apr. 2015, doi: 10.1016/S2213-2600(15)00043-0.

[26] A. Iranzo and J. Santamaría, "Severe obstructive sleep apnea/hypopnea mimicking REM sleep behavior disorder.," *Sleep*, vol. 28, no. 2, pp. 203–206, Feb. 2005, doi: 10.1093/sleep/28.2.203.

[27] J. Haba-Rubio *et al.*, "Prevalence and determinants of rapid eye movement sleep behavior disorder in the general population," *Sleep*, vol. 41, no. 2, p. zsx197, 2018, doi: 10.1093/sleep/zsx197.