Chapter 6
Feature Extraction Based on Wavelet Transform for Classification of Stress Level

Djamel Bouchaffra, Faycal Ykhlef, and Yamina Bennamane

6.1 Introduction

Traditionally, the definition of stress consists of a reaction from a restful state to an excited state in order to protect the cohesion of the organism. Classification of stress levels into different ranges (low, medium, and high) can be conducted using different sensors or instruments such as (1) galvanic skin response (GSR), (2) photoplethysmography (PPG), (3) electroencephalography (EEG), and (4) electrocardiogram (ECG). Sometimes, this task is also achieved through facial expression and speech. In the ECG domain, many approaches are proposed to classify stress. Most of these methods are based on P, QRS, and T waves due to the importance of characterizing the ventricular contractions in the human heart. The number of QRS complexes, the QRS durations, the RR distances, and the signal peak amplitudes have often been considered as relevant features for representing ECG signal. Discrete wavelet transform (DWT)-based heart rate (HR) detection algorithm is exploited for deriving HRV signals from the preprocessed ECG signal to improve stress detection (Karthikeya et al. 2013). Nimunkar et al. proposed an empirical mode decomposition (EMD) for R-peak detection [1]. A weighted total variation (WTV) denoising technique has been studied in [2] for QRS detection by preprocessing ECG signals. A regular grammar method for extracting QRS complexes has been laid out in [3]. A similar method based on DWT or identifying QRS waveforms has been introduced in [4]. The first derivative method-based Hamilton–Tompkins function and Hilbert transform for QRS identification are studied in [5]. The mother wavelet used in this latter context is the Haar function. To detect driver stress, multiple features have been utilized in [6] to achieve higher performance. In [7], after the signal

D. Bouchaffra (✉) · F. Ykhlef · Y. Bennamane
Division Architecture des Systèmes et Multimédia, Centre de Développement des Technologies Avancées, Algiers, Algeria
e-mail: dbouchaffra@cdta.dz; fykhlef@cdta.dz; ybennamane@cdta.dz

A. Khelassi, V. V. Estrela (eds.), *Advances in Multidisciplinary Medical Technologies ─ Engineering, Modeling and Findings*,
https://doi.org/10.1007/978-3-030-57552-6_6

denoising phase based on Savitzky–Golay filters, the authors relied on the isoelectric level, P wave, ST level, and QRS complex as main features for stress detection. In [8], statistical and frequency domain features of HRV have been combined seamlessly for classification of stress levels within a workplace. A sequential minimal optimization algorithm using EEG signals has been introduced in [9] to classify human stress with respect to music tracks. EEG signal-based maximum likelihood framework has also been exploited for the classification of stress at multiple levels in [10]. Another approach based on head pose features invoking different classification schemes (k-nearest neighbor, generalized likelihood ratio, and support vector machine classifiers) has been introduced in [11]. A fuzzy classifier is proposed in [12].

Furthermore, three levels of stress are detected through a fuzzy logic classifier based on features such as heart rate, skin conductance, and skin temperature information. Keshan et al. have devised different machine learning methods and algorithms to detect three levels of stress from ECG signals in automobile drivers [13]. The accuracy obtained in this latter design approaches 88.24%.

Unlike major traditional approaches cited above that are based on electrocardiogram specificities and clues such as QRS waves for feature extraction, our methodology relies on the seamless fusion of DWT analysis and statistical measures. It in fact captures the details of this type of signal. These details are indicators of abrupt changes in the ECG signals. Our approach for the classification of ECG physiological signals is novel. These latter signals represent an essential metric for getting feedback about a driver's state because they are often gathered continuously and without impeding the driver's task performance. To achieve this classification goal, we first removed noise from the original signals and then invoked discrete wavelet transform to extract a broad set of discriminative features based on the detail coefficients and statistical measures. We further applied principal component analysis (PCA) to perform feature space dimensionality reduction [14, 15]. This smaller set of features represents the input pattern to different classifiers, which are support vector machines (SVM), weighted k-nearest neighbors (WKNN), and linear discriminant analysis (LDA) for driver stress classification (refer to Fig. 6.1).

The logical organization of the manuscript is as follows: The materials and methods proposed in this research are laid out in Sect. 6.2. The obtained results and the discussion appear, respectively, in Sects. 6.3 and 6.4. Finally, Sect. 6.5 covers the conclusion and perspectives.

6.2 Materials and Methods

There are five steps that are performed to classify driver stress levels: (1) database collection, (2) signal preprocessing, (3) feature extraction, (4) feature dimensionality reduction, and (5) classification.

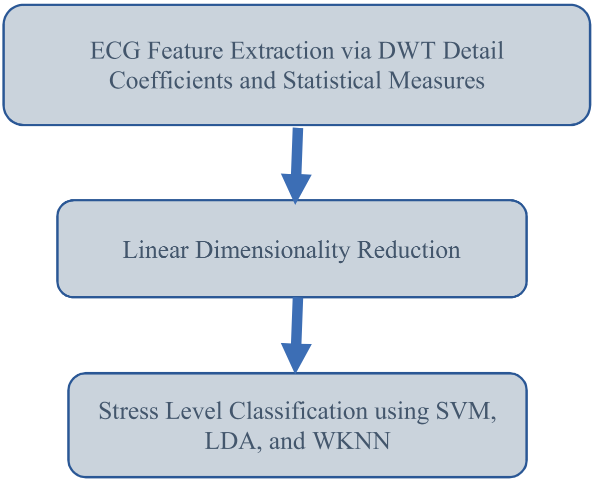

Fig. 6.1 The holistic flowchart of our methodology

Step 1. Database We have used the Stress Recognition in Automobile Drivers (SRAD) database, which is relevant for stress detection in drivers [6]. This dataset contains a set of several physiological reactions emanating from people driving on specified roads and highways, and in the following situations:

a. Low stress state or when the driver is at rest
b. Medium stressed state or when the driver is on the highway
c. High stress state or when the driver enters the city

In this experiment, we have considered only ECG information. The total driving time varies from approximately 50 min to 1.5 h, depending on road conditions.

Step 2. Signals Preprocessing This step often includes the removal of different types of noises. It has to differentiate between pure and noisy data. Only pure data are left for further analysis. Cancellation of noise has been conducted using the Wiener filter. It is well known that Wiener filter achieves noise reduction with some integrity loss of the original signal. However, this loss is often not significant in our level of analysis.

Step 3. Feature Extraction We have considered features in different domains (time, frequency, time-frequency) through the use of linear or nonlinear methods. Features normalization is often performed to minimize the inter-driver variance. In our setting, a sampled ECG signal at 496 Hz and a segment of the1-min duration ECG signal have been analyzed. We processed 120 signals for each class (class 1 represents low stress, class 2 represents medium stress, and class 3 denotes high stress). We applied DWT using the multiresolution method (MRA) on each signal, which is further decomposed into ten resolution levels. The mother wavelet that we have used is Daubechies 4 (db4). We have obtained coefficients of details and approximations. Next, we applied 12 statistical measures, which are mean, standard deviation, skewness, kurtosis, variance, root mean square, spectrum energy, Shannon

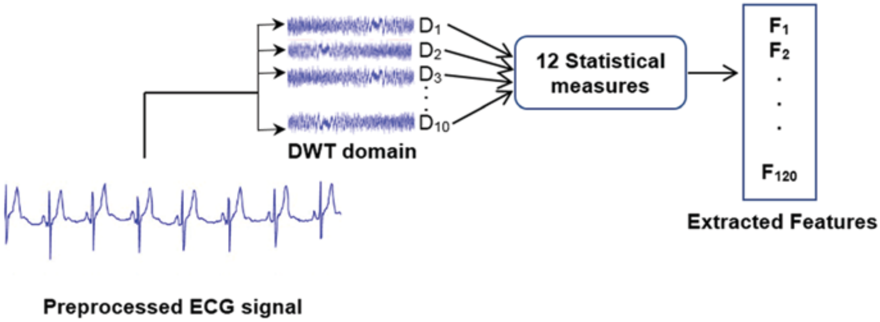

Fig. 6.2 Decomposition of the signal into ten levels using DWT: extraction of detail coefficients and statistical measures

entropy, log energy, form factor, and minimum and maximum value of wavelet coefficients. The set of detail coefficients capture abrupt changes in ECG signals (refer to Fig. 6.2).

We finally built a vector of 12 × 10 = 120 features for the ECG signals. These features are grouped and used as inputs for each classifier (refer to Fig. 6.3).

Step 4. Feature Dimensionality Reduction It often improves the performance of classifiers and minimizes computation time as well as energy costs. It is worth underscoring that some of the features we have selected are correlated: It is the role of dimensionality reduction algorithms such as PCA to recover from this issue.

Step 5. Classification After the selection of a validation set, a tenfold cross-validation is performed for prediction accuracy. This step allows predicting the class associated to a certain stress level of the driver and hence computing the global accuracy of our classifiers after averaging (refer to Fig. 6.4).

6.3 Results

As pointed out in Sect. 6.2, ECG signals used were collected from the dataset named "Stress Recognition in Automobile Drivers" available from the web repository. Training of classifiers is carried out in a MATLAB platform with a balanced dataset of 360 patterns partitioned into 120 patterns for each class (360 patterns for 3 classes). The SVM multiclass (one vs. one) is trained with the RBF kernel with optimal parameter values. Tenfold cross-validation is performed for all three classifiers SVM, WKNN, and LDA, and their accuracy is averaged within this fold. The following tables (Tables 6.1, 6.2, 6.3, 6.4, 6.5, and 6.6) depict the confusion matrices for the three classifiers with and without the application of PCA. Figures 6.5 and

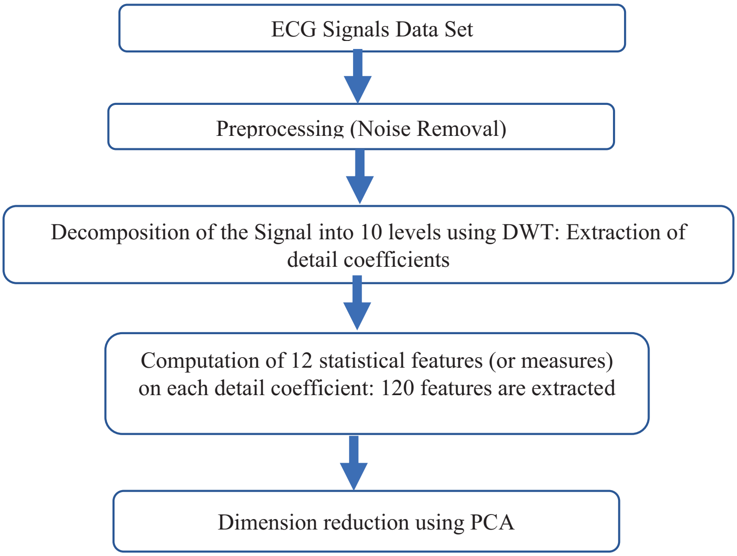

Fig. 6.3 Feature extraction flowchart

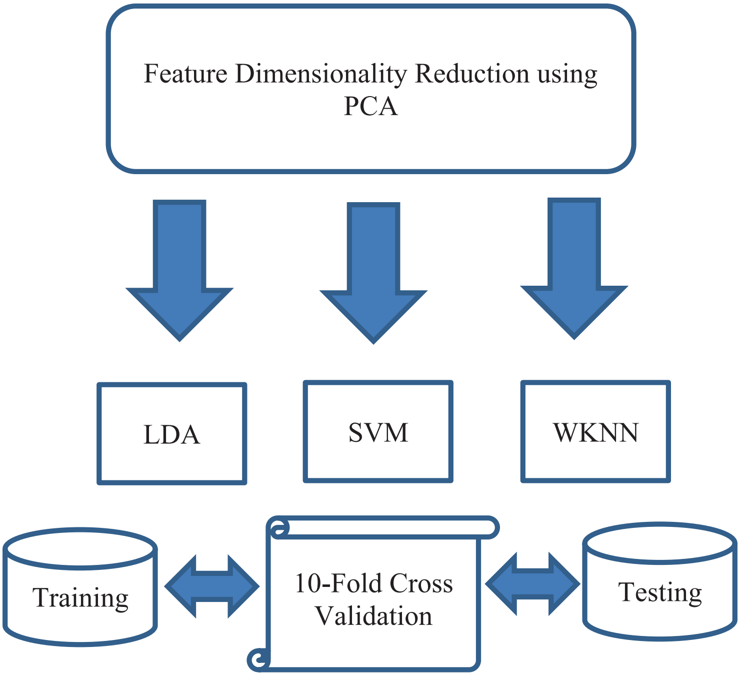

Fig. 6.4 Feature extraction and classification steps

Table 6.1 Confusion matrix of SVM with all 120 features showing an accuracy of 98.6%

	Predicted class				Rates	
		Low stress	Medium stress	High stress	TPR	FPR
True class	Low stress	118	1	1	98.3%	1.7%
		98.3%	*0.8%*	*0.8%*		
	Medium stress	1	117	2	97.5%	2.5%
		0.8%	*97.5%*	*1.7%*		
	High stress	0	0	120	100%	0%
				100%		
Accuracy		98.6%				

Table 6.2 Confusion matrix of SVM using PCA with 50 optimum number of components showing an accuracy of 95%

	Predicted class				Rates	
		Low stress	Medium stress	High stress	TPR	FPR
True class	Low stress	113	3	4	94.2%	5.8%
		94.2%	*2.5%*	*3.3%*		
	Medium stress	0	109	11	90.8%	9.2%
			90.8%	*9.2%*		
	High stress	0	0	120	100%	0%
				100%		
Accuracy		95%				

Table 6.3 Confusion matrix of LDA with all 120 features showing an accuracy of 98.6%

	Predicted class				Rates	
		Low stress	Medium stress	High stress	TPR	FPR
True class	Low stress	119	1	0	99.2%	0.8%
		99.2%	*0.8%*			
	Medium stress	2	118	0	98.3%	1.7%
		1.7%	*98.3%*			
	High stress	0	2	118	98.3%	1.7%
			1.7%	98.3%		
Accuracy		98.6%				

Table 6.4 Confusion matrix of LDA using PCA with 65 optimum number of components depicting an accuracy of 98.6%

	Predicted class				Rates	
		Low stress	Medium stress	High stress	TPR	FPR
True class	Low stress	118	2	0	98.3%	1.7%
		98.3%	*1.7%*			
	Medium stress	1	118	1	98.3%	1.7%
		0.8%	*98.3%*	*0.8%*		
	High stress	0	1	119	99.2%	0.8%
			0.8%	*99.2%*		
Accuracy		98.6%				

Table 6.5 Confusion matrix of WKNN with all 120 features showing an accuracy of 98.6% with a number of neighbors equal to 3

	Predicted class				Rates	
		Low stress	Medium stress	High stress	TPR	FPR
True class	Low stress	118	2	0	98.3%	1.7%
		98.3%	*1.7%*			
	Medium stress	0	117	3	97.5%	2.5%
			97.5%	*2.5%*		
	High stress	0	0	120	100%	0%
				100%		
Accuracy (AC)		98.6%				

Table 6.6 Confusion matrix of WKNN using PCA with 40 components showing an accuracy of 89.2%

	Predicted class				Rates	
		Low stress	Medium stress	High stress	TPR	FPR
True class	Low stress	105	13	2	87.5%	12.5%
		87.5%	*10.8%*	*1.7%*		
	Medium stress	3	114	3	95.0%	5%
		2.5%	*95.0%*	*2.5%*		
	High stress	0	18	102	85.0%	15.0%
			15.0%	*85.0%*		
Accuracy (AC)		89.2%				

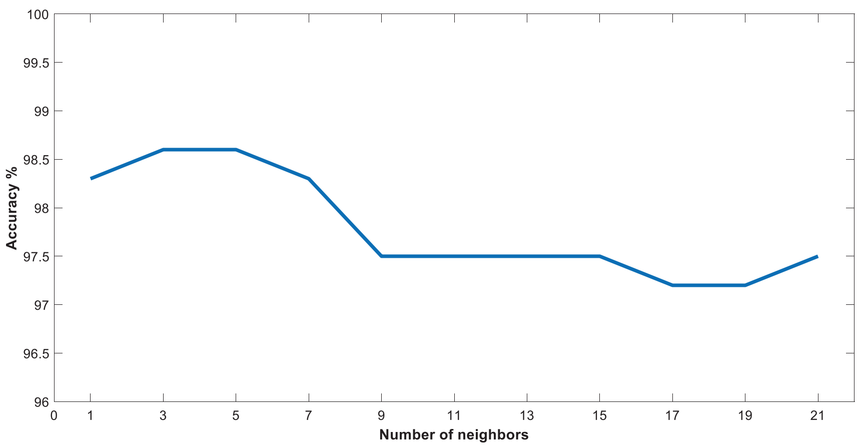

Fig. 6.5 Graph depicting the accuracy variation of WKNN classifier as a function of the number of neighbors (the accuracy is 98.6% when considering three neighbors)

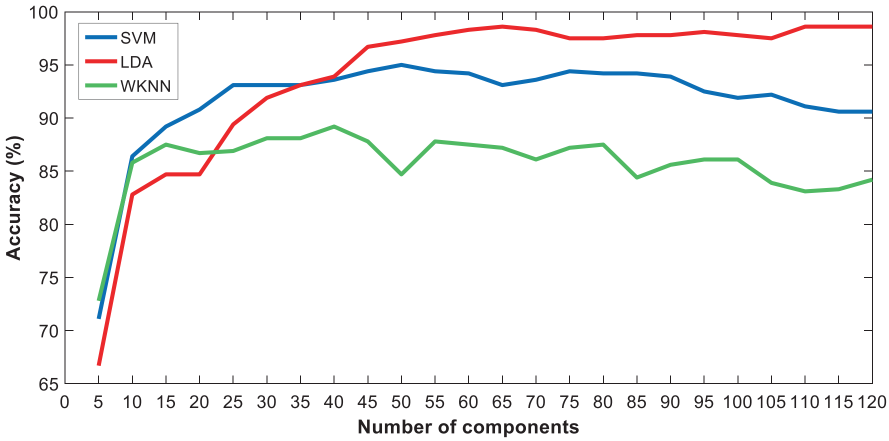

Fig. 6.6 Graph depicting the variation of the accuracy of all three classifiers (SVM, LDA, and WKNN) as a function of the number of PCA components

6.6 show the accuracy graphs with respect to some classifier parameters. The metrics used are defined as follows:

TP: True positive
TN: True negative
FP: False positive, **FN**: False negative
TPR: True positive rate
FPR: False positive rate
Accuracy = (TP + TN)/(TP + TN + FP + FN)

6.4 Discussion

This research unravels several crucial clues related to stress classification. First of all, the accuracy obtained using all features is 98.6% with all three classifiers (refer to Tables 6.1, 6.3, and 6.5). This is quite a remarkable performance when compared to the major state-of-the-art techniques. Furthermore, it is important to underscore the effectiveness of the features we have generated. It is established in the machine learning literature that strong features contribute to a high accuracy independently of classifiers' strengths. Conversely, poor features contribute to a low accuracy even if the plugged classifier is strong. It is also clear that PCA degrades the performance in the case of SVM. The accuracy fell from 98.6% down to 95% (refer to Table 6.2).

We can also point out from these results that some features are linearly correlated since PCA with only 65 components (out of 120) has been capable of achieving an accuracy of 98.6% in the case of LDA (refer to Table 6.4). Moreover, the non-parametric classifier WKNN performed quite remarkably, with only three neighbors since it has achieved an accuracy of 98.6% (refer to Fig. 6.5). However, its performance degraded when applying PCA dimensionality reduction (refer to Table 6.6 and Fig. 6.6).

Finally, Fig. 6.6 shows starting from 40 PCA components and above, LDA has achieved the best performance among all classifiers. This result highlights the data linearity captured keenly by LDA. However, SVM appears to be less affected by the variation of the number of PCA components. Indeed, SVM performs better than the other two classifiers when the number of components is less than 30. SVM performance seems to degrade using PCA, but it remained stable and robust globally.

6.5 Conclusion

Our contribution to the field is twofold: (i) feature extraction and (ii) comparison between different types of parametric (LDA) and non-parametric (SVM, WKNN) classifiers [13, 16, 17]. It appears that the use of DWT in ECG signals is worth it, since abrupt signal changes are well captured and taken into account through detail coefficients. The application of statistical measures within DWT coefficients provides an efficient framework for feature extraction. This seamless fusion between two different types of information shows promise. In order to optimize the tradeoff between computation cost and performance in ECG stress classification, one can invoke LDA as the best classifier among SVM and WKNN. However, if computation resources are available, the three classifiers can be used interchangeably, since the three of them achieved the performance of 98.6%.

Our next future work consists of combining these three classifiers seamlessly in a single multi-classifier framework to improve the global accuracy further since these classifiers do not commit errors on the same signal instances individually.

Future works can also use independent component analysis (ICA) [18, 19]. Given the expansion of the Internet of Things in healthcare, the need to combine local and global knowledge to deliver better services, the proposed system needs to contextualize and converse with others according to the type of stress involved and the person's physical conditions [20–25].

Acknowledgments This research was sponsored by the Agence Thématique de Recherche en Science de la Santé (ATRSS) under grant n°: 64/DFPR/ATRSS/2017.

References

1. A.J. Nimunkar, W.J. Tompkins, R-peak detection and signal averaging for simulated stress ECG using EMD. *The 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (2007), pp. 1261–1264
2. T. Sharma, K.K. Sharma, QRS complex detection in ECG signals using locally adaptive weighted total variation denoising. J. Comput. Biol. Med. **87**, 187–199 (2017)
3. S. Hamdi, A.B. Abdallah, M.H. Bedoui, A robust QRS complex detection using regular grammar and deterministic automata. Biomed. Signal Process. Control **40**, 263–274 (2018)
4. C.M. Khamhoo, J. Rahul, M. Sora, Algorithm for QRS complex detection using discrete wavelet transformed. Int. J. Electron. Eng. **10**, 352–357 (2018)
5. N.M. Arzeno, Z.-D. Deng, C.-S. Poon, Analysis of first-derivative based QRS detection algorithms. IEEE Trans. Biomed. Eng. **55**(2), 478–484 (2008)
6. J.A. Healey, R.W. Picard, Detecting stress during real-world driving tasks using physiological sensors. IEEE Trans. Intell. Transp. Syst. **6**(2), 156–166 (2005)
7. S. Goel, G. Kau, P. Toma, A novel technique for stress recognition using ECG signal pattern. Curr. Pediatr. Res. **21**, 4 (2017)
8. S. Srirampraksh, V.D. Prasanna, O.R. Murthy, Stress detection in working people. *The 7th International Conference on Advances in Computing & Communications*, vol. 115 (2017), pp. 359–366
9. A. Asif, M. Majid, S.M. Anwar, Human stress classification using EEG signals in response to music tracks. Comput. Biol. Med. **107**, 182–196 (2019)
10. A.R. Subhani, W. Mumtaz, M.N.B.M. Saad, N. Kamel, A.S. Malik, Machine learning framework for the detection of mental stress at multiple levels. IEEE Access **5**, 13545–13556 (2017)
11. G. Giannakakis, D. Manousos, V. Chaniotakis, M. Tsiknakis, Evaluation of head pose features for stress detection and classification. *The IEEE EMBS International Conference on Biomedical & Health Informatics* (2018), pp. 406–409
12. A.G. Airij, R. Sudirman, U.U. Sheikh, GSM and GPS based real-time remote physiological signals monitoring and stress levels classification. *The 2nd International Conference on BioSignal Analysis* (2018), pp. 130–135
13. N. Keshan, P.V. Parimi, I. Bichindaritz, Machine learning for stress detection from ECG signals in automobile drivers. *The IEEE International Conference on Big Data* (2015), pp. 2661–2669
14. I.T. Jolliffe, Principal component analysis. International Encyclopedia of Statistical Science (2011)
15. A.M. Coelho, V.V. Estrela, EM-based mixture models applied to video event detection, in *Principal Component Analysis – Engineering Applications*, ed. by P. Sanguansat, (IntechOpen, London, 2012), pp. 101–124. https://doi.org/10.5772/38129
16. R. Varatharajan, G. Manogaran, P.M. Kumar, A big data classification approach using LDA with an enhanced SVM method for ECG signals in cloud computing. Multimed. Tools Appl. **77**, 10195–10215 (2017)
17. P. Karthikeyan, M. Murugappan, S. Yaacob, Detection of human stress using short-term ECG and HRV signals. J. Mech. Med. Biol. **13**(02), 1350038 (2013)
18. F.P. do Carmo, J.T. de Assis, V.V. Estrela, A.M. Coelho, Blind signal separation and identification of mixtures of images, in *2011 Conference Record of the Forty-Third Asilomar Conference Signals, Systems and Computers* (2011)
19. R. Favilla, V.C. Zuccala, G. Coppini, Heart rate and heart rate variability from single-channel video and ICA integration of multiple signals. IEEE J. Biomed. Health Inform. **23**, 2398–2408 (2019)
20. A. Khelassi, V.V. Estrela, J. Hemanth, Explainer: an interactive agent for explaining the diagnosis of cardiac arrhythmia generated by IK-DCBRC. Med. Technol. J. **3**(2), 376–394 (2019). https://doi.org/10.26415/2572-004X-vol3iss2p376-394
21. L. Ivonin, H.-M. Chang, W. Chen, M. Rauterberg, Unconscious emotions: quantifying and logging something we are not aware of. Pers. Ubiquit. Comput. **17**, 663–673 (2012)

22. V.V. Estrela, A. Khelassi, A.C.B. Monteiro, Y. Iano, N. Razmjooy, D. Martins, D.T.M. Rocha, Why software-defined radio (SDR) matters in healthcare? Med. Technol. J. **3**(3), 421–429 (2019). https://doi.org/10.26415/2572-004X-vol3iss3p421-429
23. A. Kimmy, W. Chen, B. Lindsay, Smart photo frame for arousal feedback—Wearable sensors and intelligent healthy work environment, in *Proceedings of Workshop on Smart Offices and Other Workplaces of the 7th International Conference on Intelligent Environments*, Nottingham, UK (2011), pp. 685–696
24. E. Jovanov, A.O. Lords, D. Raskovic, P.G. Cox, R. Adhami, F. Andrasik, Stress monitoring using a distributed wireless intelligent sensor system. IEEE Eng. Med. Biol. Mag. **22**, 49–55 (2003)
25. A. Saidatul, M.P. Paulraj, S. Yaacob, N.N.F. Mohamad, Automated system for stress evaluation based on EEG signal: A prospective review, in *Proceedings of IEEE 7th International Colloquium on Signal Processing and Its Applications, Penang, Malaysia*, vol. 4–6 (2011), pp. 167–171