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VISUALISING THE SYNERGY OF ECG, EMG SIGNALS USING SOM

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***Abstract*—In this paper the normal and abnormal biosignals of ECG and EMG can be denoised and visualized in a single window for finding out the changes that occur in the abnormal signal during critical moments. The ECG/EMG signal is de-noised by using Variational Mode Decomposition and Discrete Wavelet Transform (DWT). The normal, abnormal ECG signals and normal, abnormal EMG signals are classified and viewed using Self Organizing Maps (SOM). Each signal is assigned a neuron in the output lattice of SOM. The weights are updated for the neurons according to the SOM algorithm. Euclidean distance measure is used for calculating the minimum distance between the neurons. The various normal and abnormal signals are identified and classified using SOM. Silhouette plot is utilized to check the validation of clusters.**

Keywords—Discrete Wavelet Transform (DWT), Variational Mode Decomposition (VMD), Self-Organizing Map(SOM).

I. INTRODUCTION

Viewing the synergy of bio signals in a single window aids in finding out if there are some abnormalities in the new signal compared to the previous normal signal. We have chosen ECG signals (Electrocardiogram) Fig. 2. and EMG (Electromyogram) signals Fig.1. for our experiment. ECG signals are non-stationary in nature. It is used in diagnosis of cardiac diseases. The signal is represented in Fig. 2. ECG signal has a distinct shape. These signals are generally affected by various internal and external noises. The internal noise can be due to muscular activities (EMG signal) which is the most difficult noise to be removed from the ECG signal [3]. The external noises are Baseline interference and Power line interference. The EMG signal and Power line interference are high frequency noises.

The paper is arranged in four sections. Section 1 deals with introduction to our project and literature survey. In section 2 description and methodology of the proposed system is explained. The VMD-DWT is used for the de-noising purpose since it gives a better performance in SNR value [5]. SOM is utilized for classification and viewing the ECG, EMG signals in n-dimensions based on the requirement. For example, the normal and abnormal ECG, normal and abnormal EMG of a person can be viewed in a single window.SOM is the efficient method for classification in neural networks which organizes the map according to weight changes based on input values. In section 3, the experiments and results are shown. Finally conclusions are covered in section 4.

In the study of literature related to ECG signal de-noising and classification generally Feed Forward Neural Networks and unsupervised learning were used. The fuzzy classification of ECG signal is explained in Discrete Wavelet-based Fuzzy Network Architecture for ECG Rhythm by Mohammad Reza Homaeinezhad et al in 2011. Martin Lagerholm and Carsten Peterson proposed the clustering of the ECG signal using Hermite functions in 2000. Marcel R. Risk and Jamil F. Sobh proposed the beat classification of the ECG using SOM in 1997. The k-means clustering is also used for the classification of the ECG signal. Most of these papers describe the relationships between features and classes which are the design requirements for classifier algorithms. The Neural Networks are effective in the analysis of the ECG data. It can easily classify the signals. Unsupervised learning is used for this purpose. SOM is one of the effective techniques for this classification. One can refer here to some recent studies (Talbi & Charef, 2009; Wen, Lin, Chang, & Huang,2009), which elaborate on the standard model of SOM by several interpretation-oriented features such as region analysis and feature descriptors.

The Electromyography (EMG) signal is a biomedical signal that gives an electrical representation of neuromuscular activation associated with a contracting muscle. Some clinical applications/solutions of the EMG include neuromuscular diseases monitoring, low back pain assessment, kinesiology and disorders of motor control [3]. Thus, leading to lot of R&D activities in EMG signal processing domain.

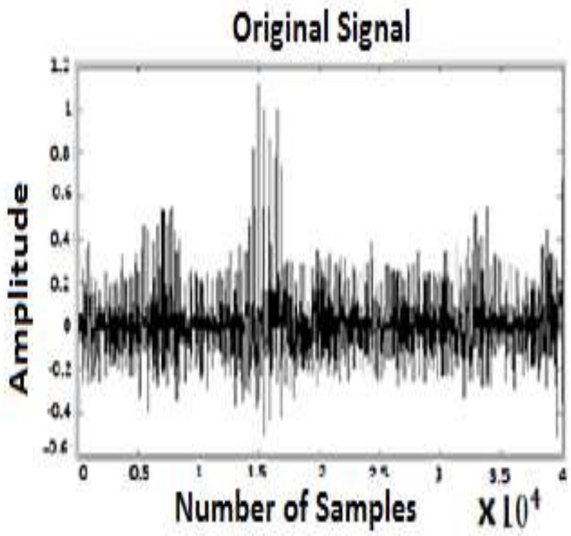

Fig 1: Normal EMG waveform

II. METHODOLOGY AND DESCRIPTION

The first stage is implemented using VMD- DWT for de-noising the ECG and EMG signal [9],[10]. EMG also contributes to the noise in ECG signal. The obtained output is given as input to one of the neuron in the SOM. Four output neurons are considered in the lattice structure of SOM. The weights are updated according to the Euclidean distance formula and the minimum distance value is obtained as the winning neuron in the structure. Winner neuron along with the neighboring neurons is updated according to the 'soft-max' rule. The 4-D weight vectors are updated and the classification is obtained. The proposed system is shown in fig 2.

A. De-noising using VMD along with DWT

The VMD is used to generate discrete number of modes (uk), by decomposing a real valued input signal. In this decomposition method, the signal is decomposed into different modes. Here an assumption is made that each mode is compact around a central pulsation (wk) [5],[6]. The center pulsation is determined along with the decomposition.

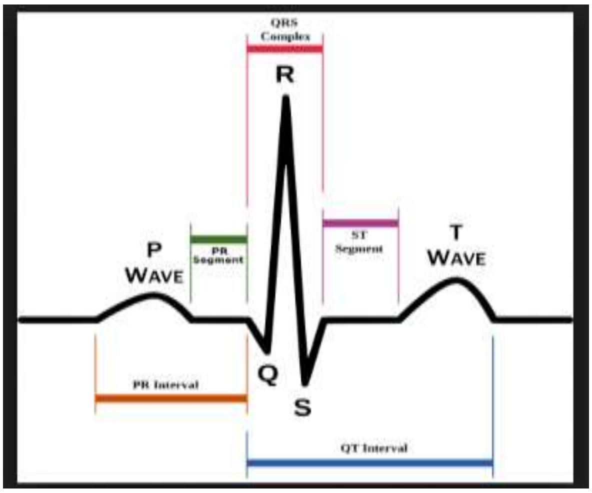

Fig.2. ECG signal representation

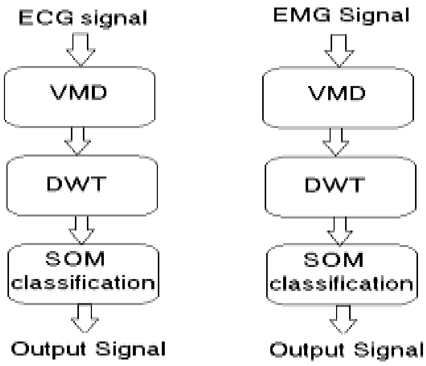

Fig.3. Proposed system

All the modes can be found out by the constrained variational problem which is defined by:

$$min(u_k, w_k) = \left\{ \left| \Sigma \partial t \left[\left(\delta(t) + \frac{j}{pi} * t \right) * uk\ (t) \right] e^{-jwkt} \right|_2 \right\} \quad (1)$$

Subject to,

$$\Sigma_k u_k = s \quad (2)$$

Where s stands for the signal to decompose, uk is the kth mode, wk is a frequency, δ is the Dirac distribution, t is a time, and * denotes convolution. Modes with lower frequency components are indicated by higher values of k.

DWT is used for de-noising the ECG signal obtained from VMD [3]. Soft thresholding is used here for the thresholding purpose because it does not sharply cut away the signal as in Hard thresholding. Fig. 4 illustrates the Filter Bank (FB) implementation of DWT. As shown in the figure, the original

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signal (S) passes through a pair of low pass h(n) and high pass g(n) filters. These filters must satisfy certain mathematical properties for reconstruction. Then outputs of each filter will be down sampled by a factor of two. Outputs of low pass and high pass g(n) filters are called approximation coefficients Ca and detail coefficients Cd respectively. Ca and Cd represents the low frequency and the high frequency components of the signal. In Wavelet Transform, the approximate coefficients are used for further decomposition as it contains more signal information. The detail coefficents are used for thresholding purpose. Let 'g' denotes high pass and 'h' low pass and the common notation:

$$Ylow[n]=\sum_{k=-\infty}^{\infty} x[k]h[2n-k] \quad (3)$$

$$Yhigh[n]=\sum_{k=-\infty}^{\infty} x[k]g[2n-k] \quad (4)$$

So the results of the DWT are a series of coefficients in one approximation and J details, where J is the number of the final decomposition level. These coefficients construct an orthogonal basis and the original signal can be reconstructed through them by applying the inverse wavelet transform (IWT). When a signal is down-sampled, the signal length is halved every time while it is passed through the filter and it allows using same pair of filter in different levels for preventing redundancy. Down-sampling plays an important part in the process of decomposition. When a noisy signal is decomposed, the signal and noise manifest differently in the post-decomposition results, making it possible to separate them by applying a threshold to the levels.

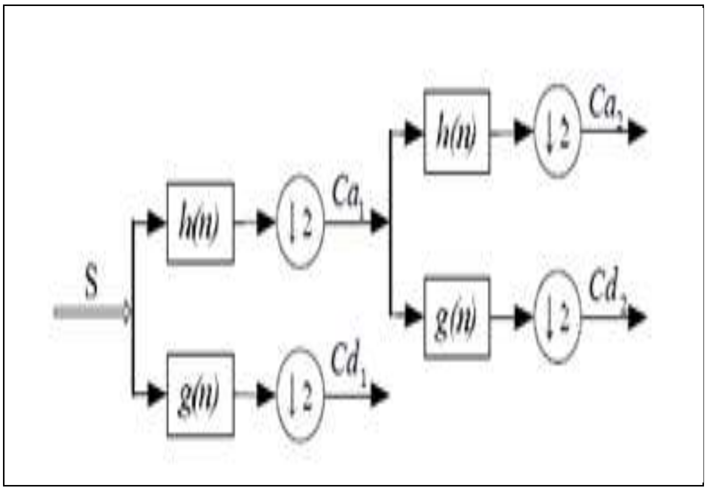

Fig. 4. Filter Bank implementation of DWT

Wavelet based de-noising procedure in general, involves three steps:

1)Decomposition: A mother wavelet and a maximum decomposition level J are chosen and the decomposition coefficients at each level are computed.
2)Thresholding: For each level the threshold values are computed (for each level separately or for the whole set of the coefficients) and applying threshold (in hard or soft process) to the coefficients at each level.
3) Reconstruction: The signal is reconstructed with the modified coefficients.

Mother wavelet, maximum decomposition level and threshold values are the three parameters selected according to these steps. Proper mother wavelet can represent signal features in a few wavelet coefficients with high magnitude that can improve thresholding and consequently, de-noising performance. Optimum mother wavelet selection can be done by using cross correlation function. The optimum wavelet maximizes the cross correlation between the signal of interest and the mother wavelet. Optimum decomposition level depends on signal and noise frequency characteristics and may be obtained by trial and error. Selection of the threshold values is the important part of de-noising procedures, where small threshold values result in noises in the reconstructed signal and the large values may eliminate some signal features.

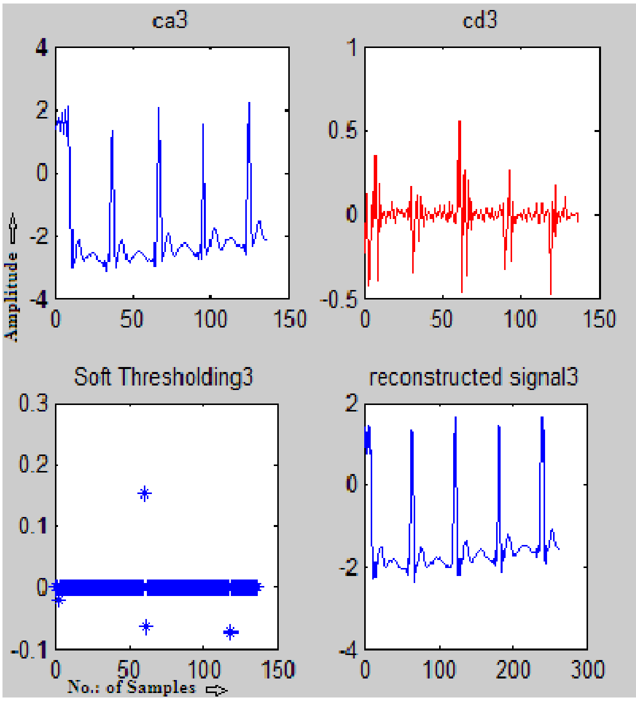

Fig.5. De-noised ECG signal

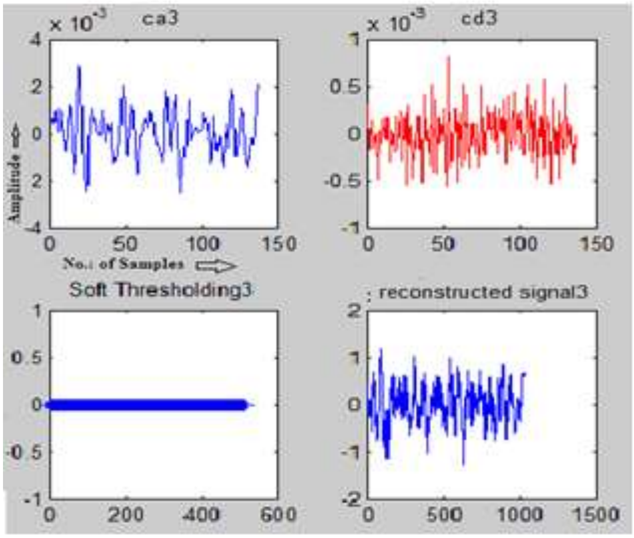

Fig.6.De-noised EMG signal

B. Classification using SOM

Self-organizing map is currently used as one of the generic neural network tools for visualization of any high dimensional data by preserving the structure [1],[7],[8]. It has a clear structure according to the weight updation. Different noises and clear signals are given as input neurons in SOM. Four neurons are given as input for the normal and abnormal signals of ECG and EMG. We are training the neurons in the network with the correct values of an ecg signal, emg signal and two other abnormal signals. Then we are doing classification of normal and abnormal signals of a test signal by updating the neighbors without changing the weights of the winning neurons.

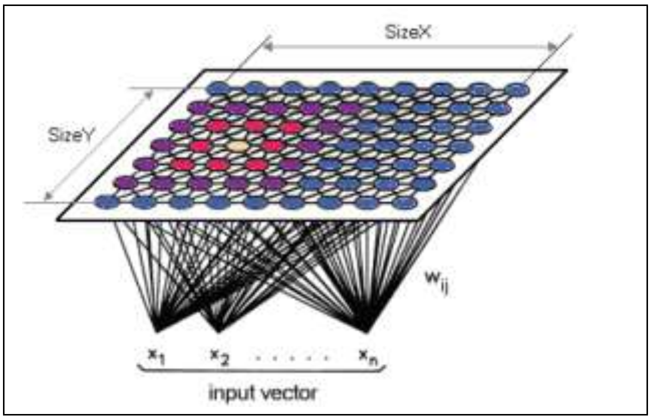

Fig.7. Representation of SOM

SOM reduces data dimensions and displays similarities among data. Several neurons compete for the current object in SOM for the clustering of data [2]. Firstly the data is entered into the system. Then the artificial neurons are trained by providing information about inputs. The weight vector of the unit closest to the current object becomes the winning or active neuron. During the training stage, the values for the input variables are gradually adjusted in an attempt to preserve neighborhood relationships that exist within the input data set. As it gets closer to the input object, the weights of the winning unit are adjusted as well as its neighbors. Like all other training networks, SOM does not require a target data. A SOM learns to classify the training data without any external supervision [2]. Getting the Best Matching Unit is done by running through all right vectors and calculating the distance from each weight to the sample vector. The weight with the minimum distance is the winner. There are numerous ways to determine the distance; however, the most commonly used method is the Euclidean Distance and/or Cosine Distance. In the proposed methodology we used Euclidean distance measure. The learning is done in several steps:

1. Initializing the weight of each node.

2. A vector is chosen at random from the set of training data.

3.The most likely weight to the input vector are examined for each node. The winning node is commonly known as the Best Matching Unit (BMU).

4. Then the neighborhood of the BMU is calculated. The amount of neighbors decreases over time.

5. The winning weight is rewarded with becoming more like the sample vector. The neighbors also become more like the sample vector. The farther away the neighbor is from the BMU, the less it learns and the closer a node is to the BMU, the more its weights get altered.

6. Repeat step 2 for N iterations.

The winner node is determined like the node with the minimum euclidian distance, computed for each node using the following expression:

$$dj=\sum_{i=0}^{N-1}\{xi(t)-wij(t)\}^2 \qquad (5)$$

Where d is the euclidian distance, j is the node index, N is the number of samples of the input vector, x is the input vector, i is the index of x vector, w is the weight vector.

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III. EXPERIMENTS AND RESULTS

The experiments of de-noising and classification are done using MATLAB software. The noised ECG signal is obtained from MIT-BIH Arrhythmia database1(data 121). EMG signal is obtained from PhysioBank ATM. The de-noised signal is obtained after VMD decomposition and DWT filtering as shown in Fig.5 & 6. The EMG signal is the most difficult noise to detect among the other noises in the ECG signal. Each of the neuron are entered into the system. The weights are updated using random values. Then according to the input neurons, further updation occurs. The neuron with minimum Euclidean distance is the winner neuron. The neighbors are also updated likewise according to soft-max rule. The different normal and abnormal signals are clearly visualized and classified using the SOM as shown in fig.7.

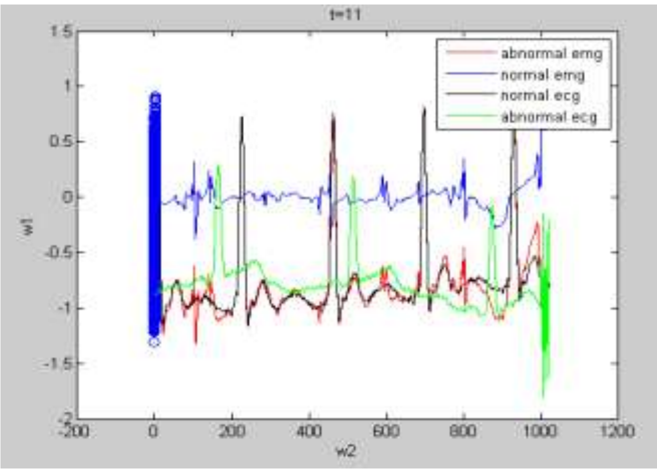

Fig.8. Various input vectors along with weight planes

The weight neurons obtained are 4-D data. The 3-D of weight values can be visualized using cftool. The fitted data are shown in fig.9 and the fitted curve in fig.8.

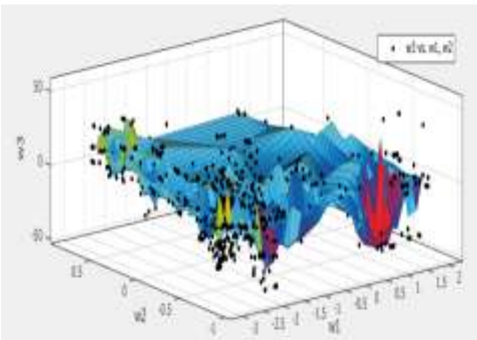

Fig.9. The fitted curve of input vectors

Fig 9 is used for visualization of 3-D values.It provides the visualization of the ECG data along with the noises.

The table 1 shows the comparison of different databases (121,100,115 and 200) using VMD-DWT for de-noising [4]. Table 2 shows the comparison of EMG signals using VMD-DWT for de-noising.

TABLE 1: CHART OF ECG SIGNALS DE-NOISED WITH VMD-DWT

Parameters dB	Database 1	Database 2	Database 3	Database 4
SNR	37.05	4.9109	15.4984	7.5044
PSNR	78.52	31.2217	35.7726	31.6482

TABLE 2: CHART OF EMG SIGNALS DE-NOISED WITH VMD-DWT

Parameters dB	Signal 1	Signal 2	Signal 3	Signal 4
SNR	6.12	5.54	5.12	5.03
PSNR	32.53	31.08	31.03	29.08

From the above de-noising charts we get a measure of the extent to which theECG /EMG signals are interrupted by the surrounding noise.

The fig. 10 shows the Silhouette plot of two signals. The Silhouette refers to a method of interpretation and validation of consistency within clusters of data. The technique provides a graphical representation of how well each object lies within its cluster. This is the silhouette plot of the clean and noised ECG data.

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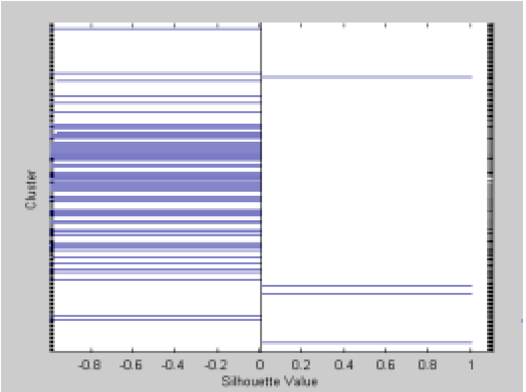

Fig.10. Silhouette plot of normal and abnormal ECG signals

IV. CONCLUSION

The de-noising of ECG signal is obtained using VMD along with DWT and the performance parameters used are SNR and PSNR. The normal and abnormal signals are separately mapped and organized in SOM by updating the weights of all the four input neurons. The result shows that the normal and abnormal signals of ECG and EMG can be viewed in a single window which can be useful for comparing the abnormalities that occur in the bio-signals. It is always desirable to have database of the normal ECG and EMG of a person so that the variations under stressed conditions can be compared.

V. REFERENCES

[1] Martin Lagerholm, Carsten Peterson, Guido Braccini, Lars Edenbrandt, and Leif Sörnmo, “Clustering ECG Complexes Using Hermite Functions and Self-Organizing Maps”, IEEE Transactions on Biomedical Engineering, Vol. 47, No. 7, July 2000.

[2] Adam Gacek, “Preprocessing and analysis of ECG signals – A self-organizing maps approach”,Elsevier, Expert Systems with Applications 38 (2011) 9008–9013.

[3] N. Ghaeb, “Simulation Study for Electrocardiography Contamination in Surface Electromyography”, International Conference Proceeding on Biomedical Engineering, pp. 1-3, 2008, 2001.

[4] Gilt George, Anu Abraham Mathew, “An ECG Signal Denoising based on VMD and Undecimated Wavelet Transform”, International Journal for Scientific Research & Development,Vol. 4, Issue 06, 2016.

[5] Yun-Chi Yeh , Che Wun Chiou , Hong-Jhih Lin, “Analyzing ECG for cardiac arrhythmia using cluster analysis”,Elsevier, Expert Systems with Applications 39 (2012) 1000–1010.

[6] Eedara Prabhakararao, and M.Sabarimalai Manikandan,“On the Use of Variational Mode Decomposition for Removal of Baseline Wander in ECG Signals”, IEEE 2016.

[7] Mohammad Reza Homaeinezhad, Ehsan Tavakkoli1 , Ali Ghaffari1, “ Discrete Wavelet-based Fuzzy Network Architecture for ECG Rhythm-Type Recognition: Feature Extraction and Clustering-Oriented Tuning of Fuzzy Inference System”, International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 4, No. 3, September, 2011.

[8] Marcelo R. Risk, Jamil F. Sobh, J. Philip Saul, “Beat Detection and Classification of ECG Using Self Organizing Maps”, Proceedings - 19th International Conference – IEEE/EMBS Oct. 30 - Nov. 2, 1997 Chicago, IL. USA.

[9] Yu Hen Hu, Senior Member, IEEE, Surekha Palreddy, and Willis J. Tompkins, “A Patient-Adaptable ECG Beat Classifier Using a Mixture of Experts Approach”, IEEE Transactions on Biomedical Engineering, Vol. 44, No. 9, September 1997.

[10] Aswathy Velayudhan, Soniya Peter , “Study of Different ECG Signal Denoising Techniques”, International Journal of Innovative Research in Computer and Communication Engineering, Vol. 3, Issue 8, August 2015