Active Control of Acoustic Noise by Magnetic Resonance Imaging: A Simulation Study

HIROFUMI NAGASHINO
Institute of Health Biosciences, The University of Tokushima, 3-18-15 Kuramoto, Tokushima, JAPAN
nagasino@medsci.tokushima-u.ac.jp http://www.tokushima-u.ac.jp

Abstract: - In medical imaging for clinical diagnosis and biomedical research magnetic resonance imaging (MRI) is one of the prevailing techniques. A lot of subjects of MRI are annoyed by the loud noise that MRI generates. In the present study computer simulation of active control of the noise induced by MRI was performed. The sound generated by the measurement sequences for the brain was recorded with an IC recorder in an MRI scanner room. Prediction of the time series of the sound was attempted using linear prediction and artificial neural networks (ANN). By subtraction of the predicted value from the sound value the sound intensity is reduced. With several optimization techniques of ANN such as steepest decent method, Levenberg-Marquadt method, etc, active control of the noise was examined. In the present paper, the comparison of the simulation results of the prediction with those methods is described.

Key-Words: - MRI, acoustic noise, active noise control, linear prediction, artificial neural networks, steepest decent method, Levenberg-Marquadt method

1 Introduction

Magnetic resonance imaging (MRI) is one of the prevailing techniques of medical imaging for clinical diagnosis and biomedical research. It employs a radio frequency magnetic field with large magnitude. A change in the Lorentz force emerges by switching of the field gradients. Such change causes alternation of contractions and expansions of gradient coils. The switching frequency is located in the rage of audio frequency. Therefore it generates loud acoustic noise that humans can hear [1], [2]. The sound intensity can be louder than 100dB.

Although new types of the MRI scanner incorporate active noise control by themselves, most of the scanners that are currently operated in hospitals do not utilize such a technique. Therefore, most subjects there have to wear earplugs or head sets as passive noise control. Nonetheless the noise annoys the subjects of MRI.

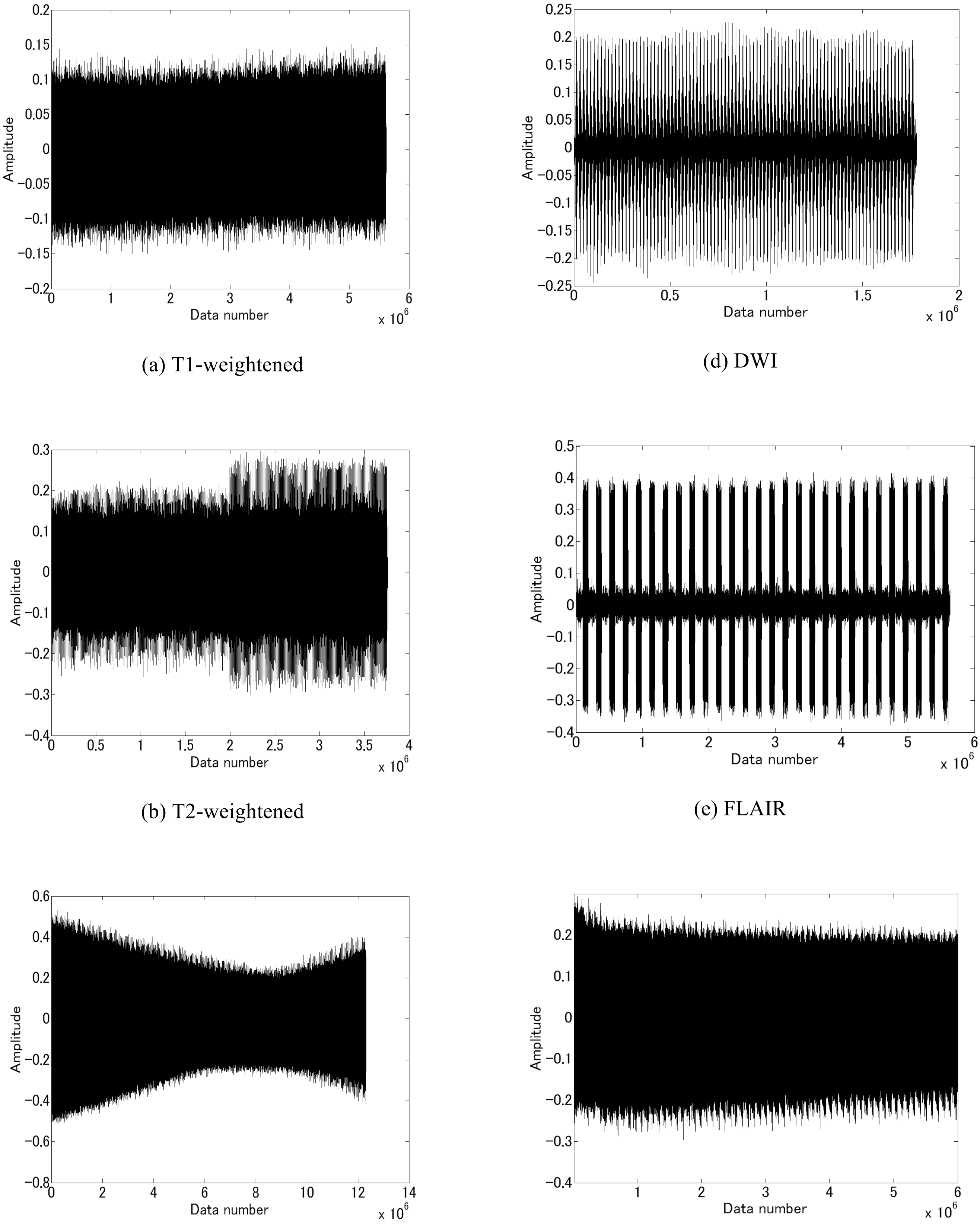
Some subjects complain of unpleasant feeling or even anxiety. Studies of physiological effects of the acoustic noise have demonstrated that exposure to loud sound of MRI could cause temporary threshold shifts, anxiety, mental fatigue, stress, fear and permanent hearing loss [3]-[5]. The influence on the human electroencephalogram also has been analyzed [6].

The research of active control of MRI sound has been conducted widely [7]-[11]. The effectiveness of linear prediction (LP) has been reported. Artificial neural networks (ANN) is one of the most effective techniques for adaptive control [12-14]. ANN can predict the time series that nonlinear systems generate. It is speculated that there is possibility that ANN gives a better performance of prediction of the sound generated by nonlinear systems than LP. MRI is one of nonlinear systems. However, the nonlinear active noise control using ANN for MRI noise reduction has not been sufficiently explored.

In the present work, a simulation study of nonlinear active control of the noise induced by MRI was performed. The sound was recorded with an IC recorder in a MRI scanner room in Tokushima University Hospital. The time series of the sound were predicted by LP and ANN. The sound intensity is reduced by subtraction of the predicted value from the sound. Several techniques of optimization including steepest decent method, Levenberg-Marquadt method, etc were examined together with ANN. In the present paper, the performance of the prediction of those methods is compared for three measurement sequences for the brain.

2 Method

A simulation study of active noise control of MRI sound associated with the measurement sequences for the brain was performed.



(a) T1-weightened

(b) T2-weightened

(c) SPGR

(d) DWI

(e) FLAIR

(f) MRA

Fig. 1. Acoustic noise by MRI.

The sound was recorded with an IC recorder in a room of MRI scanner in Tokushima University hospital. The sampling frequency is 44.1kHz.

Fig. 1 shows the waveforms of six measurement sequences, T1-weightened, T2-weightened, spoiled gradient (SPGR), diffusion weighted image (DWI), fluid attenuated inversion recovery (FLAIR) and magnetic resonance angiography (MRA).

For each time series the period was determined by calculation of self-correlation coefficient. It was employed for the determination of prediction coefficients in LP and the training of ANN.

A value in the time series was predicted from precedent three values. Other numbers of precedent values were also examined. Three values were enough to obtain good results. More values occasionally brought worse results.

2.1 Linear prediction

For linear prediction, the prediction coefficients were determined from the data in the first period of each time series. They were employed for the prediction of all the subsequent values.

2.2 Artificial neural networks

For prediction by ANN the networks were trained with the first period in each time series. That network was used for the prediction of all the subsequent values of the time series. The network is multilayered perceptron. Networks with different numbers of hidden layers and hidden units were examined.

Bacpropagation was employed for the training of the networks. Additionally optimization techniques were incorporated. Four methods for optimization, steepest decent method, Newton method, quasi-Newton method and Levenberg-Marquadt method for prediction were applied. The neural networks toolbox of MATLAB was used for this calculation. Training of the networks was stopped when the squared error is less than 10^{-6} or the number of training epochs is 4,000.

3 Results

The results of the simulation of the active control of acoustic noise of three measurement sequences for the brain are shown below.

3.1 Prediction errors

Fig. 2 shows the results of LP, and Fig. 3 shows the results of the prediction by ANN with LM. For ANN learning rate is 0.2. In the simulation for ANN, ANN with LM brought the best results. Fig. 3 illustrates the results in which the number of hidden layer is one, and the number of hidden units is 5. That network with larger number of hidden layers and hidden units did not give better results. The reason of this result could be overtraining.

For both LP and ANN simulations the root-mean-squared (RMS) value for every period of the sound data, and RMS value of the error, which is the difference between the predicted value and the sound datum value, for every period were calculated.

In the figures, the rows illustrate the changes of the RMS value of the sound data V_s, the RMS value of the error V_e, and the ratio V_e / V_s, respectively, from the top.

For T2-weightened, the RMS value of the sound data increases stepwise on the way. The error RMS value increases in connection with it. However, the error ratio does not increase significantly for LP. On the other hand, they increase for ANN.

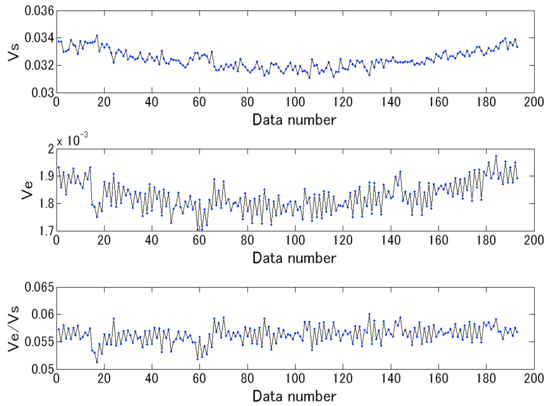
For SPGR, the RMS values of the sound data gradually decrease and after that increase again. The error ratios inversely increase and after that decrease for both LP and ANN.

3.2 Average error ratio

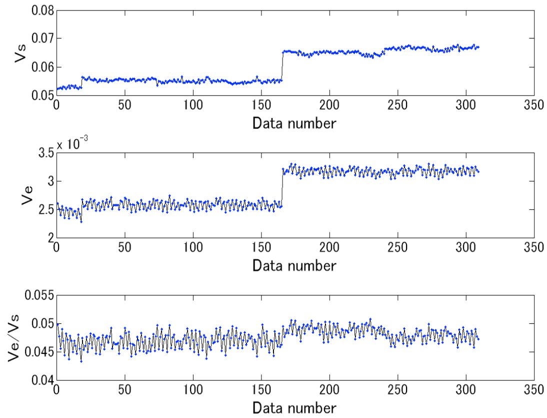
The average value of error ratios in each time series was calculated. Table 1 shows the average error ratios of LP, ANN with SD and ANN with LP. For T1-weightened sequence, DWI, FLAIR and MRA, the error ratio is slightly smaller in ANN with LM than LP. For T2-weightened and SPGR, the results are opposite. However, the difference between the error ratio for LP and that for ANN with LM is very small for each sequence. The error ratio values for T1-weightened, T2-weightened, SPGR and MRA were about 5%. Those for DWI and FLAIR were about 9% and 8%, respectively.

The error ratio in ANN with SD is much larger than those in LP and ANN with LM for each sequence. Moreover, the convergence of learning is very slow in ANN with SD. The error ratios in ANN with some other techniques are larger than those in LP and ANN with LM.

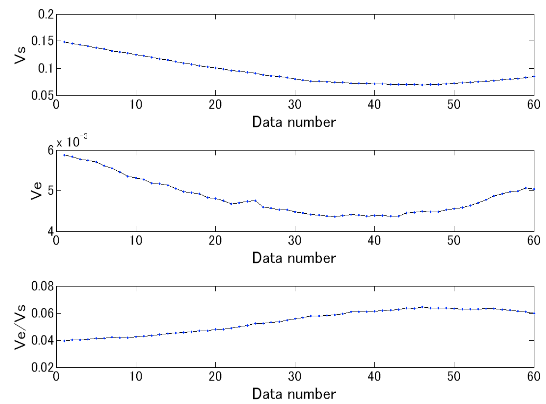
This method will be able to be applied to the noise reduction of the practical MRI facility.



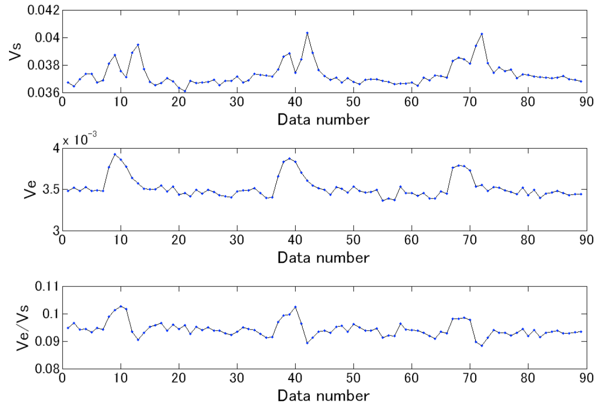
(a) T1-weightened



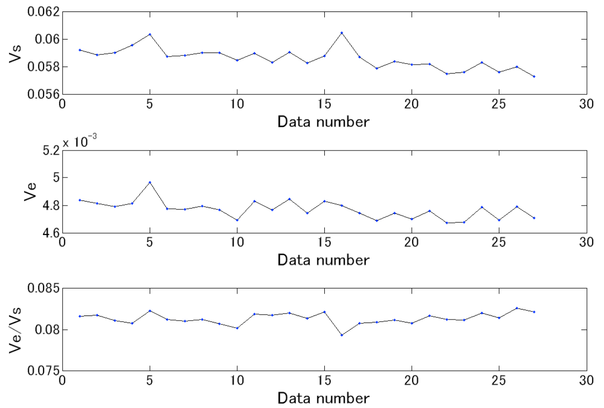
(b) T2-weightened



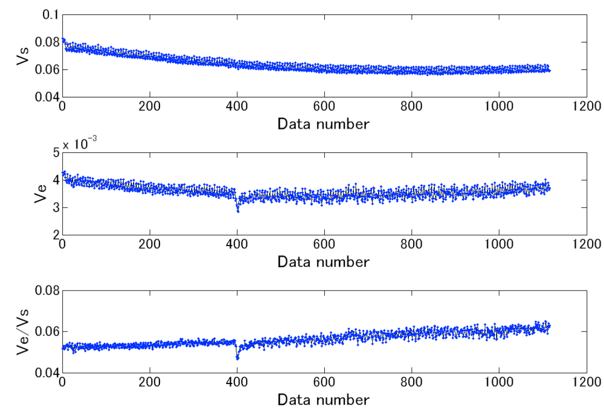
(c) SPGR



(d) DWI

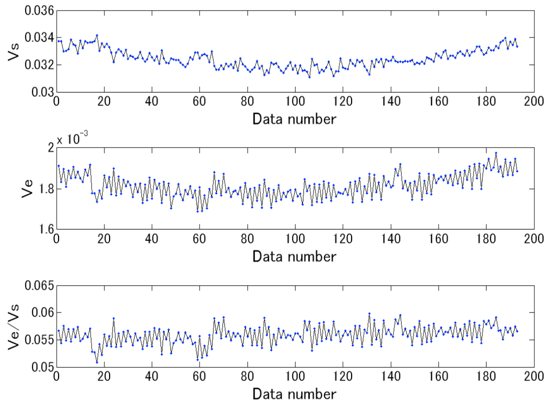


(e) FLAIR

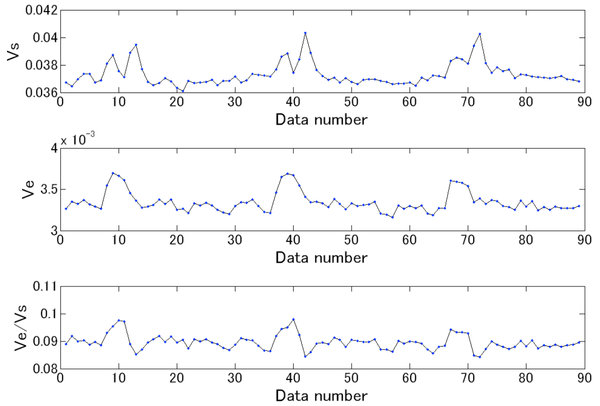


(f) MRA

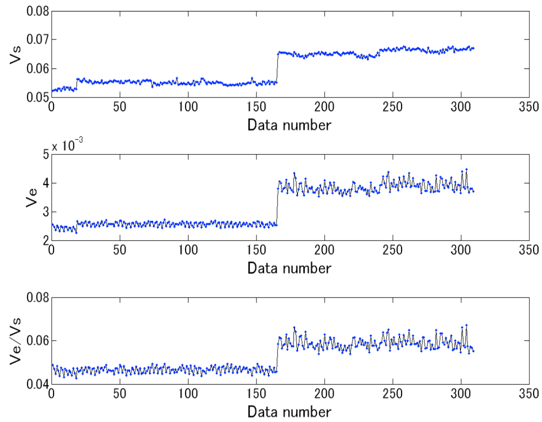
Fig. 2. Acostic noise reduction by linear prediction



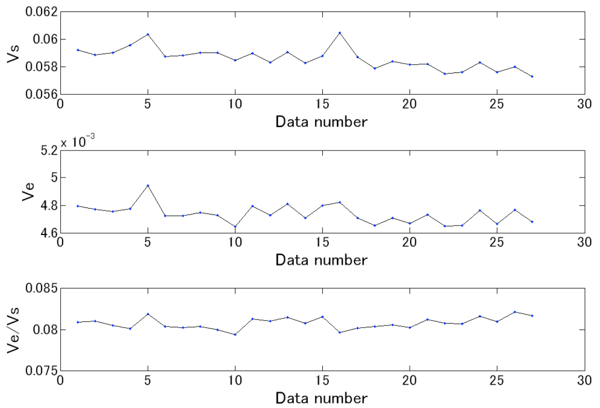
(a) T1-weightened



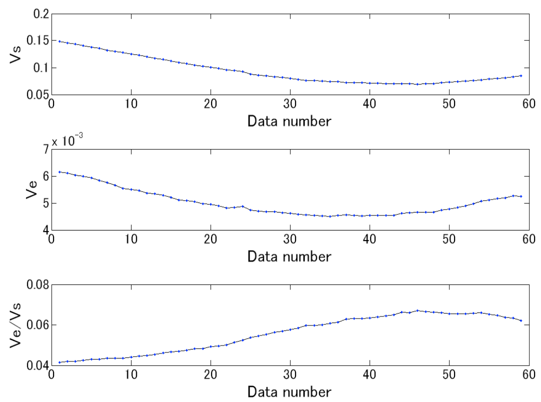
(d) DWI



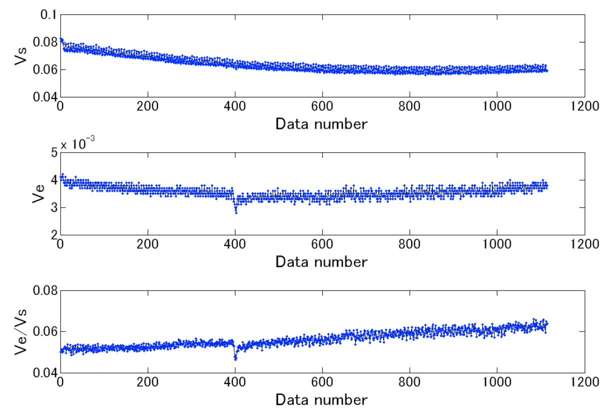
(b) T2-weightened



(e) FLAIR



(c) SPGR



(f) MRA

Fig. 3. Acoustic noise reduction by artificial neural networks with Levenberg-Marquadt method.

Table 1. Average error ratios.

Method	LP	ANN (Steepest Decent)	ANN(Levenberg -Marquardt)
T1-weightened	0.0563	0.1460	0.0559
T2-weightened	0.0475	0.1283	0.0523
SPGR	0.0539	0.2469	0.0557
DWI	0.0943	0.2452	0.0896
FLAIR	0.0814	0.6286	0.0808
MRA	0.0564	0.1457	0.0506

4 Conclusion

In the present study the performances of LP, and ANN with optimization techniques including steepest decent method (SD), Levenberg-Marquadt method (LM), etc were compared for the prediction of time series of acoustic noise in measurement sequences of an MRI scanner for the brain by computer simulation.

LP and ANN with LM gave much smaller values of error, than ANN with SD and ANN techniques with some other methods. The error values in LP and ANN with LM were similar for all the sequences.

For future work the performance of other techniques of nonlinear adaptive control will be investigated. The implementation of this method in the practical MRI facility will be also attempted.

Acknowledgments
The author thanks Koji Yamamoto for his help with computer simulation and calculation.

References:

[1] A. Counter, S. Åke Olofsson, A. Olofsson, E. Borg, B. Bjelke, A. Häggström, H. Grahn, "Analysis of Magnetic Resonance Imaging acoustic noise generated by a 4.7 T Experimental System," *Acta Oto-Laryngologica*, vol. 120, no. 6, 2000, pp. 739–743.

[2] D. L. Price, J. P. de Wilde, A. M. Papadaki, J. S. Curran, R. I. Kitney, "Investigation of acoustic noise on 15 MRI scanners from 0.2T to 3T," *Journal of Magnetic Resonance Imaging*, vol. 13, no. 2, 2001, pp. 288–293.

[3] R. E. Gangarosa, J. E. Minnis, J. Nobbe, D. Praschan, R. W. Genberg, "Operational safety issues in MRI," *Magnetic Resonance Imaging*, vol. 5, 1987, pp. 287–292.

[4] R. E. Brummett, J. M. Talbot, P. Charubas, "Potential hearing loss resulting from MR imaging," *Radiology*, vol. 169, 1988, pp. 539-540.

[5] M. McJury and F. Shellock, "Auditory noise associated with MR procedures: a review," *J. Magnetic Resonance Imaging*, vol. 12, 2000, pp. 37-45.

[6] H. Nagashino, M. Akutagawa and Y. Kinouchi, "Influence of acoustic noise of MRI on human electroencephalogram," *Proc. of International Conference on Applied Bionics and Biomechanics, Venice, Italy*, 2010, pp. BE21-BE24.

[7] A. M. Goldman, W. E. Gossman, P. C. Friedlander, "Reduction of sound levels with antinoise in MR imaging," *Radiology*, vol. 173, 1989, pp. 519–550.

[8] J. Chambers, M. A. Akeroyd, A. Q. Summerfield, A. R. Palmer, "Active control of the volume acquisition noise in functional imaging: method and psychoacoustical evaluation," *J. Acoust. Soc. Am.*, vol. 110, 2001, pp. 3041-3054.

[9] M. Li, T. C. Lim, J. Lee, "Simulation study on active noise control for 4-T MRI scanner," *Magnetic Resonance Imaging*, vol. 26, 2008, pp. 393-400.

[10] N. B. Roozen, A. H. Koevoets, A. J. Den Hamer, "Active vibration control of gradient coils to reduce acoustic noise of MRI systems," *IEEE/ASME Trans. Mechatric.*, vol. 13, 2008, pp. 325-333.

[11] M. Kuramoto, M. Kida, R. Hirayama, Y. Kajikawa, T. Tani, Y. Kurumi, "Active noise control system for reducing MR noise," *IEICE Trans. On Fundamentals*, vol. E94-A, 2011, pp. 2922-2926.

[12] Y. Lin, C. Hsu, "Adaptive wavelet neural controller design for a DC-DC power converter using an FPGA chip," *WSEAS Trans. Systems and Control*, vol. 6, Issue 1, 2011, pp. 25-32.

[13] S. I. Sulaiman, T. K. A. Rahman, I. Musirin, A. Shaari, "Evolutionary programming versus artificial immune system in evolving neural networks for grid-connected photovoltaic system output prediction," *WSEAS Trans. Systems and Control*, vol. 6, Issue 6, 2011, pp. 197-206.

[14] I. Friganiotis, P. Spanos, "On the control of micro Ball Grid Array (mBGA) production systems," *WSEAS Trans. Systems and Control*, vol. 9, 2014, pp. 67-76.