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Artifacts Prediction in 2D Ultrasound Images using Median Filter and Artificial Neural Networking

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Abstract
In general, a neural network is a device to simulate the brain. Neural network theory revolves around the idea to derive and add to simulations the core properties of biological neurons, thereby constructing a simulated (and simplified) brain. An ANN is developing through a learning process for a given application, such as pattern recognition or data classification. Training in biological systems requires modification of the synaptic connections between the neurons. For block-based image / video compression systems, blocking artifacts, characterized by visually noticeable changes for pixel values along block boundaries, may be a fundamental issue. Different post-processing methods are introduced to scale back blocking artifacts, but most usually add unnecessary blurring or ringing effects. This study provides a process for estimating cardiac motion in 2-D ultrasonic images. The problem of motion estimation is formulating as an energy minimization, of which the term of data fidelity is built on the belief that the photographs are corrupted by multiplicative Rayleigh noise. In addition to some kind of classical spatial smoothness constraint, the proposed solution takes advantage of the sparse properties of cardiac motion to regularize the response through a suitable dictionary learning stage. The proposed approach is tested on one set of data with available ground-truth like four highly realistic simulations sequences.

***Keywords:** Artifact, Artificial Neural Networks, cardiac motion, Images*

1. Introduction

1.1Artificial Intelligence

Artificial Neural Networks (ANN) are quite simple electronic models which have assisted the brain's body structure. The brain learns primarily from experience. It is natural evidence that small energy-efficient packages can also solve problems further than the reach of the current computers. Due to the advancement of computer solutions new brain modeling also ensures less technical. This modern computing approach often provides a more generous deterioration during device overload than its more conventional counterparts. Such biologically based computational approaches are consideredto the various major advances within the computing industry. Only basic animal brains are capable of functions, which computers technically cannot perform. Computers do things well, such as maintaining ledgers or doing complex maths. But computers had trouble recognizing just simple patterns that generalize certain patterns of the past far less into long-term behavior. Intelligence and ability to think, visualize, construct, memorize, and comprehend, identify patterns, make decisions, adjust to change and learn from experience. This could be the branch of technology to make machines function like humans.Thus, it is termed 'Artificial Intelligence'. Sparse-view Reconstruction will also be used to having rapid scan and decreased projection / back-projection estimation with accelerated low dose CT imaging. Given the rapid advances, picture noise and artifacts within the low dose protocol always represent a serious issue. A Deep Learning based approach called Enhanced Google Net is proposed during this paper to get rid of streak artifacts due to the missing projection in the reconstructing of sparse-view CT. In Google Search, residual learning is used to evaluate the artifacts of sparse-view CT reconstruction, thus subtracting the artifacts obtained via learning from the sparse reconstructed images, and eventually retrieving a transparent correction image. The reconstruction resolution by the proposed approach is relatively close to the projective images that are restored in full view. The results show that the approach proposed is useful and effective in minimizing the artifacts and maintaining the quality of the reconstructed image.

2. Literature Survey

For modern countries, cardiovascular diseases became the main cause for death. These are responsible with up to 45% of the total number of deaths and are expected to be successful by 2030 at around 25 million per year. [1]. The advancement of heart function assessment methods, thereby promoting the diagnosis and treatment of these diseases, is indeed of critical importance. There are a number of different ways to determine the guts ' fitness. As one of the non-invasive methods, medical imaging is used to test the mechanical operation across different modalities such as resonance imaging (MRI) and ultrasonic imaging (UI). Because of its relatively high temporal resolution, therefore, UI is much more suited to the guts' quick motion. Furthermore, it provides benefits such as low budget requirements and high patient discomfort. This allows UI the most commonly adopted modality in cardiology, especially echocardiography. The obtained ultrasound (US) images also include information which is important for determining cardiac function. US images are used either by direct visualization or by methods of post processing which extract useful qualitative and observable features. In this sense, 2D automated cardiac movement prediction additionally since related strain measurements are known to be effective tools for cardiovascular disease diagnosis [2]–[6]. Post-processing methods are said to be the main functional deblocking methods that can be done after decoding and easily integrated into any compression paradigms. They will be divided approximately into 2 categories[7], i.e. image enhancement[8] and image restoration[9]. Generally, solutions to image enhancement that plan to smooth visible artifacts instead of restore original pixel values are somewhat heuristic and no objective criteria is optimized. Furthermore, image restoration establishes the matter as an issue of picture signal reconstruction, solving wishes on observed noisy data with a few prior knowledge at the decoder. X-ray computerized axial tomography (CT) methods are commonly used for clinical diagnosis and intervention, like imaging, image-guided biopsy, image-guided intervention and significant benefits of radiotherapy. With the increased use of CT in clinical settings, therefore, the topic of radiation exposure is attracting growing attention. As a result, the requirement for a reduction in the radiation dose becomes increasingly strong under the ALARA concept (as low as reasonably achievable). With the rapid advances, picture noise and artifacts inside the low dose protocol maintains a serious issue. Equalizing image quality and dose level of x-rays has become a commonly recognized trade-off issue. In general, low dose CT is accomplished by rising tube currents (or voltage) or numbers of projections. Tube current (or tension) reduction method compromises dose reduction image quality. Projection Number reductions are accomplishing through the implementation of the sparse-view protocol for a defined scanning trajectory. In this study, the reconstruction of CT with this method is called reconstruction of sparse-view CT. Sparse-view CT reconstruction does not experience from the increased noise in projections compared with tube current or voltage reduction, and has the extra good thing regarding rapid scanning and projection / back projection calculation. However, due to missing projections, sparse-view CT reconstruction experiences from degradation of the image quality due to the increased streaking artifacts. In the last 20 years a strong effort has been made to enhance sparse-view CT reconstruction. In particular, by trying to accommodate measurement statistics, modeling data acquisition geometry, and implementing physical con-stresses, regularized iterative reconstruction algorithms often generate superior image quality with highly noisy measurements, and are thus becoming increasingly popular. In 2006, Donoho presented the idea of compressed sensing (CS) and showed that fragmented signals or piecewise images may be satisfactorily reconstructed from far less sampling data than the requirement of the Nyquist sampling theorem. Based on the CS principle, a state-of - the-art approach called (ASD-POCS) Adaptive Steepest Descent Projection onto Convex Sets [10] it is a two-way alley: As we start to use innately native methods of interacting with machines, machines also will become capable of more "human-like" behaviour. Machines will begin to use a combination of computer science (AI), Augmented Reality (AR), video game (VR) and Mixed Reality to start up an era that really begins to erase the lines between humans and machines, improving their usability and effectiveness. Among the areas where we are going to begin to work out the primary extensive use of those new interfaces is where human-to-human interaction is that the maximum. Today's scenario from an enterprise perspective are in customer care, with maximum user interactions. Customer care and employee training are pervasive across industries. These two verticals will, all told likelihood, be the primary to create HMI more supportive, rewarding and motivating [11].

3. Proposed Methodology

Deep learning using neural networks has sparked a revolution in many areas of advanced machine learning and perception. Since then, deep neural networks have performed exceedingly well across various algorithms originally developed for machine learning-based image recognition. Now, deep neural networks are expanding the potential uses well beyond image recognition, from self-driving cars to quicker development of latest drugs to real-time translation in several languages for online chats. Accelerated deep learning dramatically enhances the training process for AI systems. Faster and better inference capabilities improve the performance of Internet of Things applications, including sensor data analytics. Sensors generate large volumes of information which will, with sufficient training, be wont to predict machine malfunctions, for instance. But traditional machine learning methods can take months. Accelerated deep learning techniques, including automatic pattern recognition and reinforcement learning, decrease the time required to coach an AI system—and therefore decrease the time to actually useful inference capabilities. Figure 3 depicts a high-level view of the method flow for traditional machine learning approaches: information (i.e., images) are analyzed (feature extraction) and so identified, classified, or detected (depending on the goal of the application), and so a result's delivered to the user. The matter with this approach is that it relies heavily on human intervention for the feature extraction, identification, classification, and detection phases.

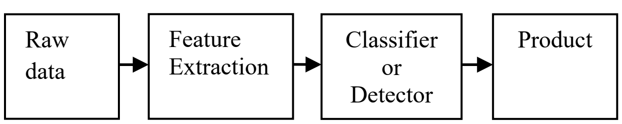


Figure 3: Process flow for traditional machine learning

3.1 Neural Network Inference

Artificial Neural Networks are a special sort of machine learning algorithms that are modeled after the human brain. That is, rather like how the neurons in our systema nervous are ready to learn from the past data, similarly, the ANN is in a position to be told from the information and supply responses within the kind of predictions or classifications.

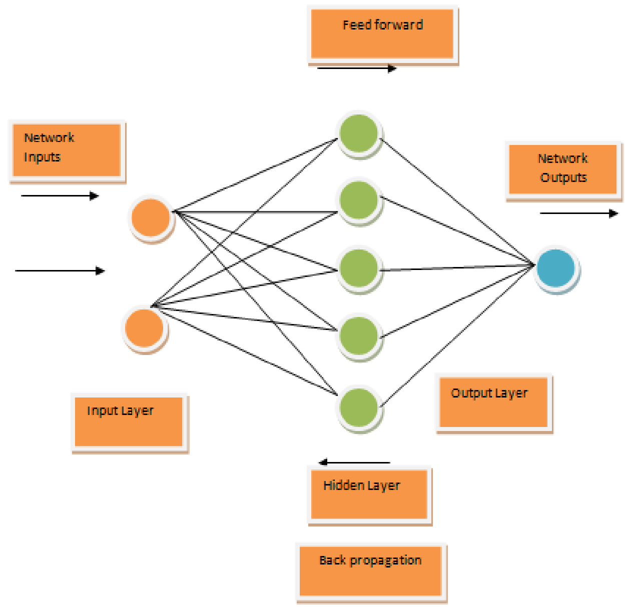


Figure 3.1: Artificial Neural Networks Architecture

1. Input Layers: That's the layer through which can provide feedback to our model. After this layer the quantity of neurons is an adequate maximum number of features in our data (number of pixels incase of an image).
2. Hidden Layer: The input is then fed into the hidden layer from the input layer. Based on our layout and the data size there can be several hidden layers. Every hidden layer will have specific neuron numbers that are usually greater than the amount of features. That layer's output is determined by matrix operation of the previous layer's output with learnable layer weights and by adding learnable biases supported by activation function making the network non-linear.
3. Output Layer: The output from the hidden layer is further fed into a logistic function such as sigmoid or softmax that transforms each class output towards a probability score for each class.

Deep learning neural networks demand extraordinary processing power because deep learning involves lots of vector and matrix operations. Using customized deep learning cores can result in stellar performance for neural network processing implementations. However, for developing new networks, it's also valuable to be able to work within a typical framework that creates the method of testing and modifying networks fast and light-weight. A full description of the artifacts prediction steps is given in algorithm 1.

```
%% Classification
% Put the test featurs into variable 'test'
test = FEAT;
load net1
 y = round(sim(net1,test));

% Visualize Results
if y == 1
msgbox('Atrial septal defect')
elseif y == 2
msgbox('Dilated_cardiomyopathy')
elseif y == 3
msgbox('Left ventricular dysfunction')
elseif y == 4
msgbox('Mitral stenosis')
elseif y == 5
msgbox('Atrial septal defect')
elseif y == 6
msgbox('Normal')

end

%
classifier2 = {'ENDPOINT ERROR (IN mm, VOXEL SIZE 0.7×0.9×0.6 mm3) AND AVERAGE EXECUTION TIMES (IN s) FOR THE 3 SEQUENCES OF HIGHLY REALISTIC SIMULATIONS'};
T = table(LADprox,normal,Rca,Time)
```

3.2Artificial Neural Network

```
% load the data
load FEAT1
load FEAT2
load FEAT3
load FEAT4
load FEAT5
load FEAT6
load FEAT7

T=[FEAT1 FEAT2 FEAT3 FEAT4 FEAT5 FEAT6 FEAT7];
x=[1 2 3 4 5 6 7];

% create a feed forward neural network
net1 = newff(minmax(T),[500 40 1],{'logsig','logsig','purelin'},'trainrp');
net1.trainParam.show = 1000;
net1.trainParam.lr = 0.01;
net1.trainParam.epochs = 7000;
net1.trainParam.goal = 1e-6;

%train the neural network using the input,target and the created network
[net1] = train(net1,T,x);
%save the network
save net1 net1

%simulate the network for a particular input
y = round(sim(net1,T));
```

Feat1

Mean Longitudinal Strain Values

3.3 Simulation Output

Feat 1

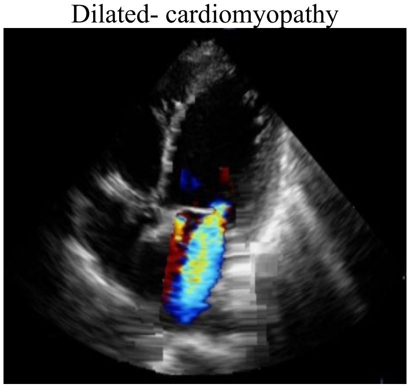
Atrial septal defect

T =

LADprox	normal	Rca	Time
0.41932	0.99875	0.22415	0.19394

Feat 2

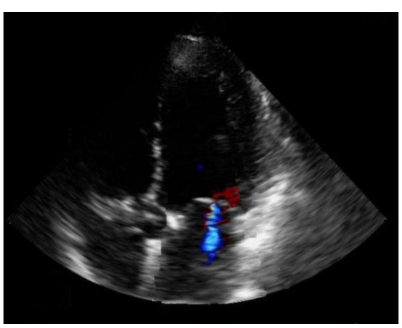
Dilated- cardiomyopathy



T =

LADprox	normal	Rca	Time
0.13114	0.97296	0.12649	0.43836

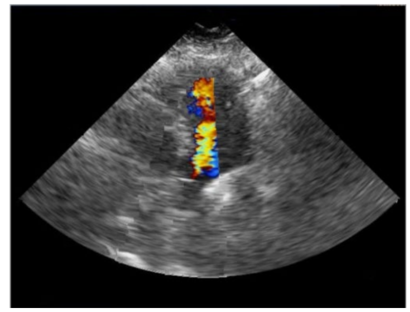
Feat 3



T =

LADprox	normal	Rca	Time
0.30536	0.99525	0.21004	0.20189

Feat 4

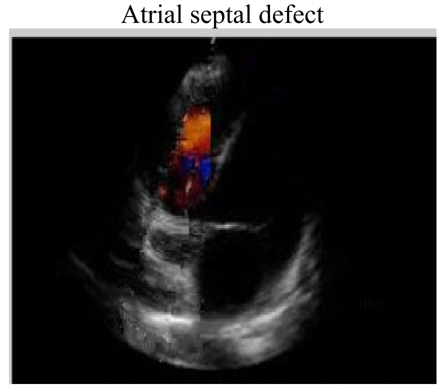


T =

LADprox	normal	Rca	Time
0.22407	1	0.21908	0.19133

Feat 5

Atrial septal defect

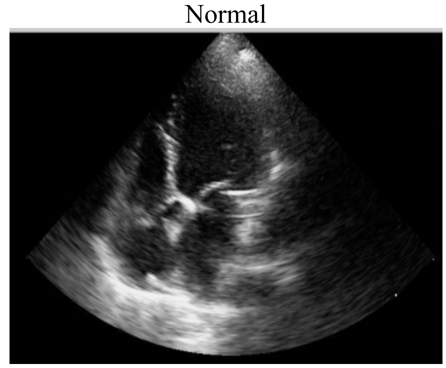


T =

LADprox	normal	Rca	Time
0.41932	0.99875	0.22415	0.19394

Feat 6

Normal



T =

LADprox	normal	Rca	Time
0.072353	0.97568	0.2184	0.20031

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4. Conclusion

This acceleration is vital because researchers or people working with deep learning will want to experiment with multiple deep learning architectures as an example, the quantity of layers, cost functions, regularization methods. The proposed system also normalized the motion by using a regularization smoothing method to help the motion field gradient and by using a previously adopted DL sparse motion. Our study also found that those regularizations are efficient for estimating cardiac motion. As regards motion and strain precision, the results obtained with highly realistic simulations showed this approach's competitiveness with respect to state-of - the-art approaches. The results of this study on actual data show the technique is in line with a clinical understanding synonymous with photographs of stable and unhealthy subjects.

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