

Development of Cardiac Prescreening Device for Rural Population Using Ultralow-Power Embedded System

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Abstract—The invention is inspired by the desire to understand the opportunities and expectations of developing economies in terms of healthcare. The designed system is a point-of-care (POC) device that can deliver heart-care services to the rural population and bridge the rural–urban divide in healthcare delivery. The product design incorporates several innovations including the effective use of adaptive and multiresolution signal-processing techniques for acquisition, denoising, segmentation, and characterization of the heart sounds (HS) and murmurs using an ultralow-power embedded Mixed Signal Processor. The device is able to provide indicative diagnosis of cardiac conditions and classify a subject into either normal, abnormal, ischemic, or valvular abnormalities category. Preliminary results demonstrated by the prototype confirm the applicability of the device as a prescreening tool that can be used by paramedics in rural outreach programs. Feedback from medical professionals also shows that such a device is helpful in early detection of common congenital heart diseases. This letter aims to determine a framework for utilization of automated HS analysis system for community healthcare and healthcare inclusion.

Index Terms—Adaptive signal processing, biomedical signal processing, cardiovascular system, data acquisition.

I. INTRODUCTION

MEDICAL practitioners use cardiac auscultation for an objective clinical screening of cardiac conditions and prediagnosis. It is, however, noted that a real-time system for the same is conspicuously lacking in development. The non-stationary nature of cardiac signals also makes the generation

of a robust system for heart sound (HS) analysis difficult. Diagnosing heart diseases using stethoscope and ECG are two fundamental approaches due their efficiency, simplicity, and noninvasiveness [1]–[3]. HS auscultation highly depends on the hearing ability, skill, and experience of a cardiologist [1]. In real time, lung sounds interfere with the HS making it noisy, which leads to increased difficulty in diagnosis of heart diseases using signal-analysis techniques. An integrated HS analysis tool thus becomes vital to assist the cardiologist [2]. Study shows that in developing countries, cardiologist-to-population ratio is 3:10 000 and is highly biased toward urban areas, thus creating a rural urban divide in cardiac healthcare. The designed device also enables a paramedic to contribute significantly in rural healthcare in case of unavailability of a trained physician, and in prescreening programs.

The presently available electronics stethoscopes like HD Medical-HDfono and 3M Stethos are aimed for educational and training purposes. In literature, reference of devices for cardiac prescreening and diagnosis using HS are rare.

In the present study, we use a Texas Instruments' Mixed Signal Processor (TI-MSP 430) based handheld device to innovate and develop a Point-of-Care (POC) heart care and patient monitoring system that can be used for noninvasive cardiac screening. This system is utilized in determining human subjects susceptible to cardiac ailments or showing early symptoms, thus mitigating early diagnosis and enabling a demographic study of cardiac cases. In future we plan to integrate the system with Microsoft CE-SQL-based patient database management system and haptic interfaces using Microsoft Windows CE for easy operation.

II. SYSTEM ARCHITECTURE

Cardiology is a grand challenge in healthcare and has inspired in envisioning the design concept with several intended benefits including low cost semi real-time analysis of data, door to door recording services enabled by mobile or ultramobile devices, demographic data prediagnostic input, and expert intervention in case of emergency through GSM/GPRS networks.

A. Target Specifications

Several technological innovations are built in into the system prototype: 1) development based on ultralow-power embedded processors (TI-MSP 430); 2) expert intervention of medical practitioners by remote monitoring at tertiary healthcare centers; 3) the system incorporates state of the art-denoising

Manuscript received July 22, 2010; accepted August 2, 2010. Date of publication October 21, 2010; date of current version February 18, 2011. Asterisk indicates corresponding author.

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Digital Object Identifier 10.1109/TBME.2010.2089457

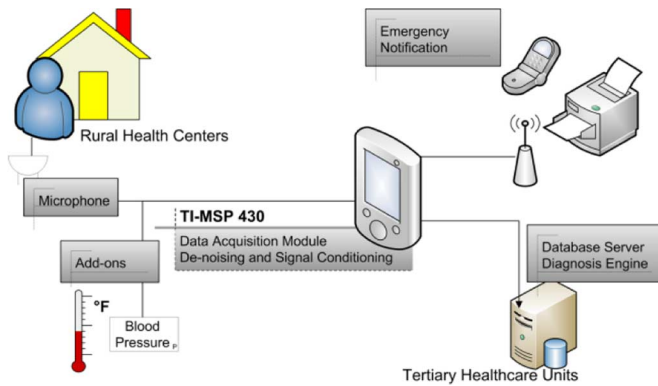


Fig. 1. System workflow: The model contains three major modules- 1) data acquisition using handheld device (POC), 2) preprocessing and screening based on TI-MSP430 embedded within POC, 3) diagnostics at central server based at Tertiary Healthcare Unit, which incorporates expert feedback and clinical decision making tools. The diagram also shows device capability of supporting add-on devices and networking through GSM/CDMA network.

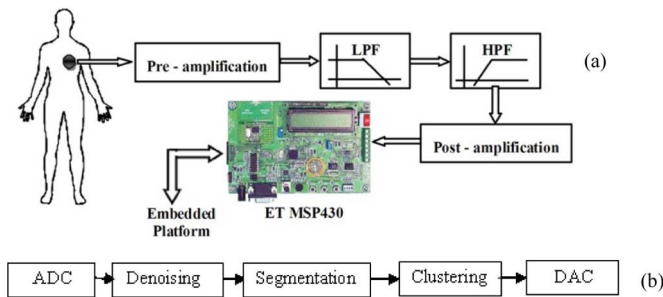


Fig. 2. Block diagram of system in design: (a) high-level diagram of the embedded assembly, and (b) computational steps within TI-MSP 430.

algorithms suited for field use in the rural nonclinical setup; 4) the data analysis is based on physiological considerations and medical domain knowledge has been employed for classifying the signal in four preliminary classes that includes normal and three abnormal conditions (see Fig. 1).

We aim to optimize the device capabilities both *in vivo* and *in vitro* by making the design and development cycles flexible and adaptive. As depicted in Fig. 2, TI-MSP430 is the heart of the system; it handles the role of data acquisition as well as signal processing for the input composite signal. The preamplification unit consists of a low-pass filter (LPF) and high-pass filter (HPF) circuit. This LPF-HPF circuit in combination with the amplification unit forms the signal conditioning block that performs the primary filtering operation to delimit the unnecessary components of the input signal. It also amplifies the signal of interest to an extent so that it can be properly gated to the input of TI-MSP430 [3]. It is, however, not able to deinterlace the overlapped heart and lungs sounds for which wavelet-based denoising is introduced in the processing unit. Postamplification unit comprises the signal conditioning block that performs the filtering operation to remove the unnecessary region of the input signal and amplifies the signal of interest. The signal-processing algorithms are implemented on the TI-MSP430 to minimize lung sounds, ambient noise, and acoustical distortions.

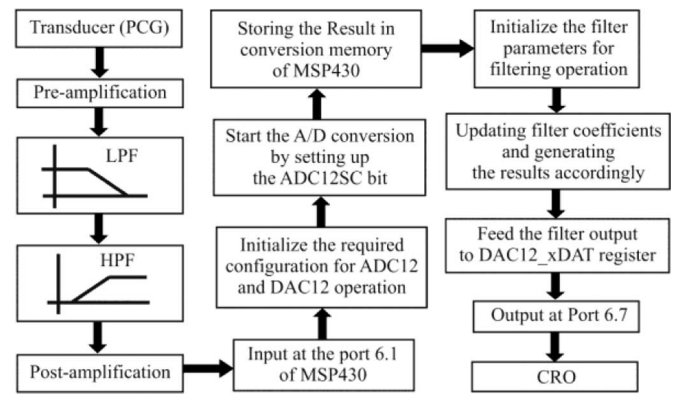


Fig. 3. Block diagram of system hardware.

Finally, when the signal is fed into TI-MSP430, it samples the analog input, applies the signal-processing algorithms, and separates the HS signal from the lung sound accordingly. The signal is segmented for each beat and clustered based on its frequency and temporal features.

B. Hardware Platform: TI-MSP 430 and Its Advantages in Embedded Applications

The internal architecture of TI-MSP 430 comprises of multiple analog and digital modules through which CPU can communicate with the external interfaces and devices. Several features make the TI-MSP430 suitable for low-power and portable applications. The CPU is small and efficient with a large number of registers. Several low-power operating modes reduce power consumption and extend battery life. There is a wide choice of clocks: from the low-frequency watch crystal to high-frequency digitally controlled oscillator (DCO).

The hardware module provides RS232 and RS485 for communicating with computer, audio inputs and outputs, switching applications, etc., to make the system versatile.

C. Hardware Implementation

The schematic of the system including the steps for implementation of the algorithms has been depicted in Fig. 3. The HPF-LPF circuit designed in the present instrumentation consists of a 4th order Butterworth Low Pass Filter (cut-off ~ 1000 Hz) and a 4th order Butterworth High Pass Filter (cut-off ~ 20 Hz). The Sallen-Key Topology is used for filter design because of its inherent gain accuracy. Moreover, Butterworth filter provides a satisfactorily flat pass-band magnitude response and attenuation of ~ -3 dB at the cut-off frequency (see Fig. 4).

The implementations of the algorithms are carried out in the IAR workbench (V 5.4), using "C" language given its simplicity and versatility in embedded programming. The programs are compiled in the TI-MSP430 IAR C/C++ compiler. Both A/D and D/A operations are performed in low power mode (LPM0) that draws a power $\sim 95 \mu A$. This feature of the program reduces the power consumption at the time of A/D and D/A conversions. The CPU only commands over the filtering program during

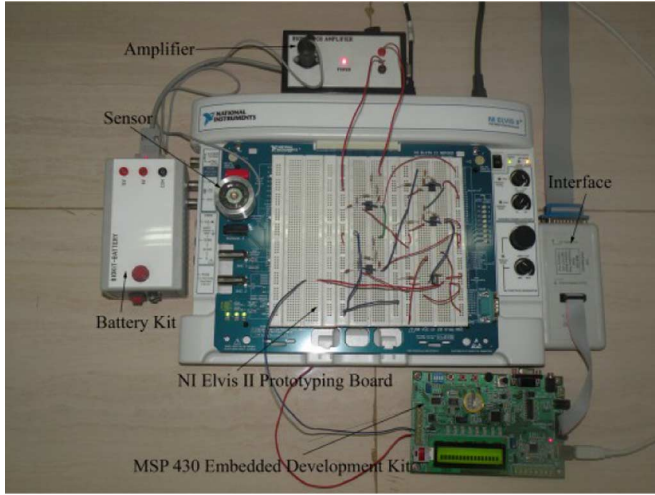


Fig. 4. Prototype of the system built with NI Elvis.

which the TI-MSP430 switches from low power mode to active mode ($I \sim 600 \mu A$).

In the first stage of algorithm, all the proper settings for ADC, DAC and port 6 are initialized. The ADC process is established by setting the ADC12SC bit. The sample values are fed to the input of the filter algorithm. For faster operation, the filtering process is executed with high clock frequency. The filtered signal data is accumulated in the DAC12_1 data register for D/A operation. The process continues iteratively, and whenever a sample value comes to the input buffer of the filter it modifies its array, performs filtering operation and channelizes the result to the DAC12_1 data register. DAC output can be obtained at the port 6.6 pin and is been gated to the LCD for visual inspection.

III. SIGNAL DENOISING AND SEGMENTATION

There are several signal-processing schemes requiring a separate noise reference for denoising of HS adaptively. This study is based on approaches where single channel is required for HS denoising. In designing the embedded device, we have used two classes of algorithms for denoising: 1) adaptive signal-processing algorithms, and 2) multiresolution signal processing using wavelets [9].

A. Adaptive Line Enhancer

The adaptive line enhancer is a system that is used frequently in biological signal processing to extract the desired biosignal from the background wideband noise [4]–[8]. Its reference signal, instead of being derived separately, consists of a delayed version of the primary (input) signal. The delay is provided to decorrelate the noise signal so that the adaptive filter (used as a linear prediction filter) cannot predict the noise signal while easily predicting the signal of interest. Thus, the output will contain only the signal of interests, which will be again subtracted from the desired signal and the error signal will then be used to adapt the filter weights to minimize the error. We implement the ALE model using the least mean square (LMS) algorithm and the recursive least square (RLS) algorithm.

B. Wavelet-Based Denoising

It is observed that orthogonal wavelet transform compresses the energy in a signal into few large components, whereas the noise is disorderly and characterized by small coefficients scattered throughout the transform. We can neglect these smaller coefficients from the wavelet-decomposed details, and thus, reduce the noise [10]. In DWT, the energy content is concentrated in larger wavelet coefficients from that we can easily reconstruct back the original signal.

1) *SureShrink*: *Sureshrink* is a smoothness adaptive algorithm and works at multiple levels of wavelet decomposition and uses the principle of Stein's unbiased risk estimator (SURE) for risk estimates [11]. For our application, we modified the *SureShrink* algorithm and parameterized the equations to reduce computational cost.

2) *BayesShrink*: *BayesShrink* is a wavelet shrinkage method that has emerged much earlier and is outperformed by newer emergent techniques. The same is, however, included in the study because of its computational cost efficiency that make it better suited for fast real-time and embedded operations.

C. Segmentation of HSs

The signals are decomposed to level 5 using Daubachis 6 (db6) wavelets. The detail coefficients of levels 4, 5, and 6 are used for the calculation of Shannon's entropy. The subbands are scaled and added up to give a partial reconstruction.

The normalized Shannon's entropy is calculated from the signal and is used to generate the signal envelope. The same is then passed to a peak detector. The subbands are scaled up and added to give a partial reconstruction that amplifies the S1–S2 factors. In case we have a detected peak, we pass on the data to a boundary-calculation algorithm else recalculate the peak points by readjusting the threshold adaptively. Other entropy measures are being employed and evaluated including fuzzy entropy, Kapur's entropy, and approximate entropy measures. The measures for envelop detection presents an interesting comparison, however, the same lies beyond the scope of the present article (see Fig. 5).

IV. PERFORMANCE EVALUATION

The data were acquired *in situ* using the instrumentation designed. Total 72 samples were obtained from 17 volunteers. The evaluation is based on the comparison of the power spectral density (PSD) of the signals both at the input of the systems and the output of the systems for LMS-ALE and RLS-ALE, and wavelet methods. HS_{recover} and $NOISE_{\text{reduction}}$ are computed in terms of percentages (see Table I)

$$HS_{\text{recover}} = \left(\frac{1 - E \{x_{\text{HS}}^2(n)\} - E \{y^2(n)\}}{E \{x_{\text{HS}}^2(n)\}} \right) \times 100\% \quad (1)$$

$$NOISE_{\text{reduction}} = \left(\frac{E \{x_{\text{hs_noi}}^2(n)\} - E \{y^2(n)\}}{E \{x_{\text{hs_noi}}^2(n)\}} \right) \times 100\% \quad (2)$$

TABLE I
PERFORMANCE ANALYSIS OF LMS-ALE, RLS-ALE, AND WAVELET METHODS

Methods	HS Recovery (%)	Noise Reduction (%)
LMS -ALE	91 – 93	89 – 92
RLS - ALE	95 – 97	90 – 92
<i>SureShrink</i>	96-98	91-92
<i>BayesShrink</i>	96-98	88-91

where $x_{HS}(n)$ is the original HS, $x_{hs_noi}(n)$ is the HS corrupted with noise signal, and $y(n)$ is the output recovered signal after application of the filtering techniques. It is evident that LMS and *BayesShrink* algorithms are able to recover the HS signal from wideband noisy background with sufficient accuracy. However, the performance of the *SureShrink* and RLS-ALE algorithm is much better than the LMS-ALE and *BayesShrink*. The e-General Medical and the Texas Heart Institute online datasets were also employed for validation of the methods using synthetically added white Gaussian noise (see Fig. 6).

V. CLASSIFICATION AND ITS CLINICAL SIGNIFICANCE

The system is designed to classify the signals into: 1) abnormal and 2) normal classes at the onset. The abnormal classes once screened are further classified into: 1) valvular heart diseases (VHD), 2) ischemic heart disease (IHD), and 3) abnormal undetermined (AbU). The subclassification is based on frequency signatures of the HS and its temporal properties. The valvular disorders can be easily picked up by identifying the murmurs in the segmented HS. When concomitant ECG-PCG signal recordings are studied, we can find the evidence of atrial fibrillation. Ischemic heart diseases can be diagnosed when there is an early or late heart failure, S3 Gallop, or a loud P2 (loud P2 often indicates a pulmonary hypertension); an atrial septal defect is indicated by a split of second HS. Coronary stenosis is generally known to produce sounds due to turbulent flow of blood in the occluded arteries. Normally, the sounds are masked and are not audible clearly during the systolic phase but the same can be picked up by precision sensors during the relatively quiet diastolic phase [5]. The extraction of useful information from the diastolic sounds associated with coronary occlusions using the adaptive signal-processing algorithms and the use of clinical examination variables can yield encouraging results. The signals are highly attenuated and complex so high precision microphones are required to detect the sound signals. The feature vectors extracted from the diastolic sounds analyzed, in addition, other physical examination variables like pulse rate, ambient/body temperature, and patient details are registered using the system that can be used by fuzzy and neural network classifiers located at a remote server to validate the results and minimize false detections.

The clustering of the systolic and the diastolic segments are done with the help of K -means algorithm[♠] [12], where $K = 2$, a fuzzy inference engine[†] is used to incorporate the data from the other peripherals (see Table II for results). The frequency

TABLE II
FALSE POSITIVES AND FALSE NEGATIVES (FP + FN)

Detection Errors	Normal	VHD	IHD	AbU
Total Samples	14	14	14	22
Cardiologist	1+3	1+0	2+3	3+3
♠ Classifier1	2+2	1+2	2+2	7+6
† Classifier2	1+2	1+1	1+1	5+4

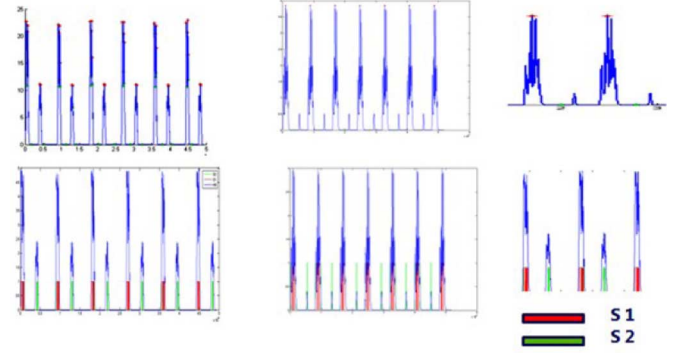


Fig. 5. Peak detection for segmentation: (a) normal HS, (b) aortic insufficiency; segmentation based on energy: (c) normal, (d) peak detection for normal, (e) aortic insufficiency, and (f) segmentation cycles.

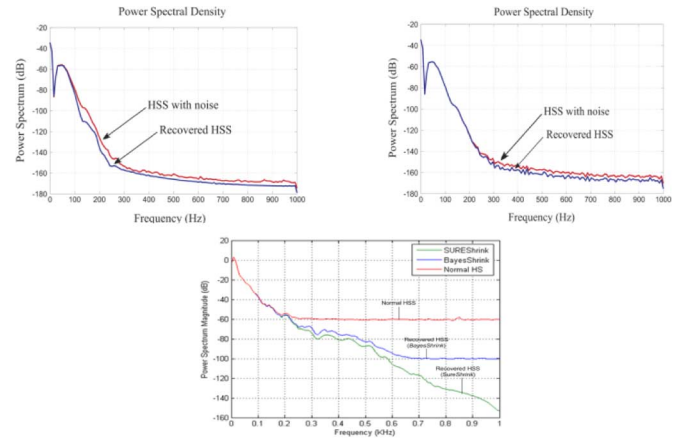


Fig. 6. Power spectrum densities for: (a) LMS-ALE, (b) RLS-ALE, (c) *SureShrink*, and *BayesShrink* applied over acquired PCG datasets.

features were determined with reference to the S1 and S2 peaks determined using the entropy plots (see Fig. 5).

The applicability of the system can further be extended to pediatric heart care and can be used for early detection of ventricular septal defect (VSD), bicuspid aortic valve disorders and patent ductus arteriosus (PDA). As per statistics, 2–5 children are detected with congenital heart defects per 1000 live births. Hence, use of a noninvasive and safe methodology, i.e., auscultation, for identification of these conditions can provide a paradigm shift in pediatric and neonatal healthcare.

VI. CONCLUSION

The presence of any abnormality in the subject's heart alters the temporal domain signature of the HS, and accordingly, it can be sensed by the device. These latent changes in the signal are

monitored in a real-time basis after processing on TI-MSP430. The system has a special color scheme to indicate a patient risk; further, a networked cardiologist is alerted for any abnormalities in the recorded HS. This system design facilitates the use as a POC device owing to its properties of portability and real-time operation. It is primarily aimed to identify the population suffering from various heart ailments through sufficient screening enabling early detection leading to timely diagnosis, and targeted remedial measures. The methodology thus developed is the core technology for a rural heart care delivery and diagnosis system in form of an embedded handheld device, which can be carried to the village households ensuring sustainable healthcare delivery.

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