Autonomous Cardiac Diagnostic based on Synchronized ECG and PCG Signal

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1 STAGE OF THE RESEARCH

The MIPS Laboratory (Modelling, Intelligence, Process and Systems) is an interdisciplinary research laboratory hosted by the Haute Alsace University. It is involved in several research projects that deal with signal processing, software engineering, microscopy imaging and modeling and identification in automatic and mechanic.

Since March 2012, the MIPS laboratory is involved in the telemedicine project E-care (www.projet-e-care.fr) piloted by the NEWEL society. This project rallied economics and scientific community to keep patients in the comfort of their own home with a higher level of care and all this with reduction cost.

The E-care project aims to develop best practices and a platform for awareness raising, knowledge exchange and policy making in this field. The project is closely linked to the thesis contribution of Ali Moukadem (Moukadem, 2011). Indeed, this thesis fulfilled in MIPS laboratory and HUS "Hôpitaux Universitaires de Strasbourg" co-financed by "region Alsace" and ANR ASAP TLOG 06 project, became interested in development of robust methods for heart sound analysis which can be used for auto-diagnosis and telemedicine applications.

Diagnosis based PhonoCardioGram (PCG) signals alone cannot detect all cases of heart symptoms (Ahlstrom et al., 2008). In this work, we are recommended for using an EleCtrocardioGram (ECG) signal besides a PCG signal for heart disease investigation. The advantage of the proposed system is that a heart's diagnosis system based on the ECG and PCG signals can lead to high performance heart diagnostics (Ping and Zhigang, 1998).

This thesis project, brings economic and scientific partners together, is financially supported by "Caisse des Dépots" and "region Alsace" and seeks to improve the use of telemedicine for life saving. The activities planned focus on providing good practices and improving the quality of services offered to patients.

2 OUTLINE OF THE E-CARE PROJECT

Despite considerable advances in medical therapy, heart failure remains a substantial burden of mortality and economic cost (EUROPEAN.COMMISSION, 2012). These trends underline the growing fiscal and medical imperative to develop better strategies to improve care delivery to heart failure patients and reduce rehospitalization rates.

The healthcare reform in many countries generates new approaches to care delivery and to provide high quality. The main reflect is the need for improving the access of a growing aging population in order to contain the costs (Zannad et al., 2009).

At the present, the societal and economic benefits from wider use of telemedicine are far from being achieved (Weinstein et al.). Then politicians and healthcare leaders are realizing that telemedicine is clearly a buttress of the solution. This is tangibly seen by the soaring number of healthcare systems that are adopting telemedicine, by the development of industry investments in telemedicine products and involvement of government in project delivery. There common goals is to initiate the citizens on keeping them healthy, partly by encouraging them to become more active participants in their own health management.

Telemedicine provides healthcare services through use secure transmission of medical data and information for the diagnosis, prevention, treatment and following up patients focusing in benefits of advanced current technologies and the advance in signal processing field.

Heart failure (HF) is among the major causes of hospitalization for elderly citizens (Zannad et al., 2009). The New York Heart Association (NYHA) (www.heart.org) functional classification of HF is widely used classification system relating HF symptoms. The NYHA classification consists of four categories that range from no symptoms (class I) to severe at rest (class IV).

The E-care project's, through telemedicine, main objective is to greatly contribute to the enhancement of the remote patient monitoring, expanding the possibilities for lifesaving care. In this project, a smart platform is adopted for home monitoring using noninvasive sensors to HF patients with NYHA (class III) severity. This platform is open and extensible to integrate data sources, to complete the patient knowledge which will help in diagnostic and report the risk at an early stage.

Our contribution in this project, with our partners, is to enhance the signal processing part for accurate diagnostic. Although ECG and PCG signals play important roles in heart abnormality detection, diagnosis based alone on ECG signal or PCG signal cannot detect most cases of heart symptoms. Hence, some research has focused on diagnosing heart defects based on the intercourse between ECG and PCG signals (Jabloun et al., 2013); (Phanphaisarn et al., 2011); (Ahlstrom et al., 2008) which can bring high performance heart diagnostics.

Unlike the time or frequency methods, the time-frequency analysis has the advantage of being robust in heart sounds segmentation (Moukadem et al., 2013). Thanks to this advantage, we want during this thesis to expand the scope applications to ECG signals and see also to find common features between the two signals.

3 HARDWARE AND DATA ACQUISITION

Chosen sensor are from the market and validated "Continua" to ensure the compatibility with E-care platform. A lot of new system will come on the marquet on the feature, but we focus our attention only on commercialized product so we work with aquared signal from system that could be used by cardiologist.

A laptop will be used as data acquisition for the proposed analysis. A measurement campaign will be carried out in the cardiology department of the HUS of Strasbourg. Heart sound will be captured using the electronic stethoscope (Littmann Electronic Stethoscope Model 3200), figure 1. An ECG (éolys), figure 2, amplifier circuit will be used to capture and amplify the ECG of patients. Both are wirelessly connected to the laptop.

3.1 Phonocardiogram Signals

Phonocardiogram (PCG) is the acoustic recording of mechanical activity of the heart. It facilitates the measurement of the instantaneous heart rate, beat-to-beat differences and duration of systolic and diastolic phases. These measures provide information about the cardiac function.

Figure 1: 3M™ Littmann® Electronic stethoscope model 3200.

The Littmann electronic stethoscope, figure 1, is intended for medical diagnostic purposes. It is used for the detection and amplification of internal sounds in human body such as from the heart, arteries, veins, and other internal organs using selective frequency ranges. It is designed to be used by anyone who wishes to listen to a sound which is known, in medical terms, as auscultation.

Using its Bluetooth wireless link, the stethoscope exchange audio data with an external device in real time, permitting their visual presentation, recording, and analysis by applications software.

3.2 Electrocardiogram Signals

The heart produces tiny electrical impulses which spread through the heart muscle to make the heart contract.

Figure 2: Electrogradiogram éolys®.

The éolys® electrocardiogram (ECG), figure 2, record the electrical activity of the heart from electrodes on the body surface. To measure the rate and regularity of heartbeats, the ECG includes 12 self-adhesive electrodes attached to selected locations of the skin on the arms, legs and chest.

There is for wirelessly transmitting a 3-/6- or 12-channel ECG to a monitor, e.g. a PC or a regular patient monitor.

4 SIGNAL PROCESSING METHODS

In this experiment, the two physiological signals (ECG and PCG) will be collected simultaneously but without electronically controlled synchronization of the measures.

Advanced methods and techniques of signal processing and artificial intelligence will be applied to extract relevant features, after the acquisition, from the two physiological signals. These signals are non-stationary by nature. The classical Fourier transform analyzes the frequency content of signal without any time information. Therefore, the importance of time-frequency transforms to detect the frequency changes of signal over time and to extract pertinent features form the two physiological signals.

4.1 S-Transform Challenges

In recent years, joint time and frequency representation provide a better description of signals in time-frequency planes. Therefore, the time-frequency analysis for non-stationary signals is of great interest and importance in evaluation of signal characteristics. Mathematical tools of time-frequency analysis include short-time Fourier transform (STFT), Wigner-Ville distribution (WVD), wavelet transform (WT) (Daubechies, 1990) and recently Stockwell Transform (S-Transform) (Stockwell et al., 1996). S-Transform leads to multiresolution signal processing, which is considered as a variable sliding window STFT or as phase corrected WT.

Stockwell et al., introduced in 1996 the S-Transform. It combines the potential of the Short Time Fourier Transform (STFT) and continuous wavelet transform (CWT) and provides an alternative approach to process the non-stationary signals. It employs a moving and scalable localizing window length. The frequency dependent window function produces sharper time localization at higher frequencies and higher frequency resolution at lower frequencies. Furthermore, the S-Transform has an advantage, even at the presence of high level of noise (Stockwell et al., 1996,); (Mansinha et al., 1997), in that it provides multi-resolution analysis while it is capable of obtaining reasonably accurate amplitude and phase spectrum of the analyzed signals.

The S-Transform of a time series $h(t)$ is defined as

$$S(\tau,f)=\int_{-\infty}^{+\infty} h(t)\frac{|f|}{\sqrt{2\pi}}\exp\left(-\frac{(\tau-t)^2 f^2}{2}\right)\exp(-i2\pi ft)\,dt \quad (1)$$

where $\frac{|f|}{\sqrt{2\pi}}\exp\left(-\frac{t^2}{2\sigma^2(f)}\right)$ is the Gaussian modulation function and $\sigma(f)=\frac{1}{f}$ is the standard deviation.

where f is the frequency, t and τ are both time.

The continuous wavelet transform $W(\tau,d)$ of a function $h(t)$ is defined as

$$W(\tau,d)=\int_{-\infty}^{+\infty} h(t)\,w(t-\tau,d)\,dt \quad (1)$$

The S-Transform of the function $h(t)$ can also be defined as a wavelet transform with a specific mother wavelet multiplied by a phase factor

$$S(\tau,f)=W(\tau,d)\exp(i2\pi f\tau) \quad (2)$$

where the mother wavelet $w(t,d)$ is defined as

$$w(t,f)=\frac{f}{\sqrt{2\pi}}\exp\left(-\frac{t^2 f^2}{2}\right)\exp(-i2\pi ft) \quad (3)$$

where the dilation d function is the inverse of f. the inverse of S-Transform is given by

$$h(t)=\int_{-\infty}^{+\infty}\left[\int_{-\infty}^{+\infty} S(\tau,f)\,d\tau\right]\exp(i2\pi ft)\,df \quad (4)$$

and, since $S(\tau,f)$ is complex, can be written as

$$S(\tau,f)=A(\tau,f)\exp(i\theta(\tau,f)) \quad (5)$$

where $A(\tau,f)$ and $\theta(\tau,f)$ are the amplitude and the phase of the S-spectrum respectively. The phase spectrum is an improvement on the wavelet transform in that the average of all the local spectra does indeed give the same result as the Fourier transform.

The S-Transform is a useful time-frequency analysis algorithm. However, it still suffers from poor energy concentration for the most classes of signals. An optimization to the existing S-Transform can enhance the energy concentration in the time-frequency domain.

In this perspective, as part of my thesis, the first line of work can be articulated on two theoretical approaches presented in the following two paragraphs.

4.1.1 Windows Width Algorithms

Modification of the window width of the S-Transform enhances the energy concentration in the time-frequency domain. Djurović et al., (2008) proposed an algorithm to optimize the window width in the S-Transform based on the measure of concentration (Stanković, 2001), which quantitatively evaluates the energy concentration. Sejdić et al., (2007) use the Kaiser windows for improving the energy concentration of the S-Transform.

4.1.2 Time-frequency Reassignment and Synchrosqueezing

The Heisenberg uncertainty principle limits the resolution that can be attained in the time-frequency plane; different trade-offs can be achieved by the choice of time-frequency family transform, but none is ideal. Then the representation can influence the interpretation given on the time-frequency plane in order to deduce properties of the signal.

To overcome this difficulty, new techniques, reassignment (Auger and Flandrin, 1995) and synchrosqueezing (Daubechies and Maes, 1996), are recently emerged as a powerful signal processing tool in non-stationary signal processing. Its basic objective is to provide a sharper representation of signals in the time-frequency plane and extract the individual components of a non-stationary multi-component signal. These techniques are widely used in several of new domains, such as audio (Fulop and Fitz, 2006), physics (Kotte et al., 2006), ecology (Dugnol et al., 2007), or physiology (Auger et al., 2013).

4.2 Features Extraction by Time-frequency Correlation

Some heart problem know as mitral stenosis, manifested through a heart sound known as the Opening Snap (OS), is very similar to the third heart sound (S3). Then, it is very difficult to distinguish these two sounds without going through proper training (Erikson, 1997).

In the E-care project we are interested by detecting the fourth heart sound (S4). The fourth heart sound is a low-pitched sound and it occurs shortly before the first heart sound that makes it detection difficult. For the purpose to study the fourth heart sound we explore two methods based on correlation with optimized S-Transform. These methods can make the detection most effective.

The first method includes a cross-spectral analysis to study the source localization and phase synchrony of non-stationary signals (Assous and Boashash, 2012); (Stockwel, 2007). Since the S-Transform localizes spectral components in time, the cross correlation of specific events gives the phase difference and the amplitude of the cross S-Transform indicates coincident signals. As the local phase information can be extracted from the S-Transform, we can use the cross S-Transform function to analyze the in-phase and the out-of-phase components in time-frequency space. This is a very useful characteristic for cross-spectral and phase synchrony.

The second method consists on pattern recognition. The basic idea is to correlate the signal being analyzed with known template and make decisions based on the magnitude of the correlation coefficients, which is between 0 and 1. The process of correlation is essential to determine the degree of similarity between the signal being analyzed and the template. A proposed scheme (Sejdic and Jin, 2007) known as Selective Regional Correlation (SRC) has been developed for band limited nonstationary signals. The preprocessing is carried out by converting a one-dimensional (1D) time-domain signal into a two-dimensional (2D) time-frequency domain representation. The redundant representation of a (1D) signal in a (2D) time-frequency domain can provide an additional degree of freedom for signal analysis to overcome the intertwined time domain features of the signal and allowing more importance in the time-frequency domain, resulting more effective pattern matching.

5 EXPECTED OUTCOME

Using time-frequency reassignment, synchrosqueezing and correlation function could makes detection method more effective and accurate in complex condition with heavy background noise.

In order to perform the knowledge of the heart activity for automated heart diagnosis and heart disease investigation, we think that using two physiological signals (ECG and PCG) could be efficient. Both ECG and PCG signals can thus be used together for early stage detection of heart disease into E-care platform.

In this work, an automated system for preliminary heart defect detection is proposed. This system is based on the concept of time-frequency signal analysis.

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