Association of Ankle Brachial Pressure Index with Heart Rate Variability in a Rural Screening Clinic

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Abstract

Peripheral vascular disease (PVD) can be associated with atherosclerosis and/ or peripheral neuropathy, which can be characterized by impairment of sensory, motor or autonomic nervous system. A noninvasive test to detect PVD is the ankle brachial pressure index (ABPI). Autonomic nervous system function can be determined by assessing heart rate variability from an ECG recording. No clear association between PVD and cardiac autonomic dysfunction has been demonstrated to date.

Over 800 records of individuals attending a diabetes complications screening clinic were analyzed. ABPI was determined from the ankle and brachial blood pressure recordings. Ten minutes 3 lead ECGs were also recorded as well as age, gender and blood pressure. HRV was determined using linear and nonlinear measures. A Decision Guidance Management System (DGMS) was applied to identify novel associations between HRV and ABPI. The number of participants in the low tertile range HRV, increased significantly as ABPI increased from 1.0 to >1.2 (p=235).

This is the first time a consistent association between ABPI and HRV in asymptomatic individuals has been shown suggesting that HRV can be used as a surrogate marker for identification of PVD and indicates a pathophysiological relationship between PVD and autonomic nervous system dysfunction.

1. Introduction

Cardiovascular disease (CVD) comprises both rhythm and vascular pathology. The autonomic nervous system, which consists of both sympathetic and parasympathetic components can have an influence on, or be influenced by vascular factors such as endothelial function. For example, large artery stiffness, which is a cause of peripheral vascular disease (PVD), is associated with increased sympathetic activity and conversely arterial stiffness can impair baroreflex activity [1]. Asymptomatic PVD can be identified using the ankle brachial pressure index (ABPI). Clinical decisions based on ABPI are made more difficult due to the differences in opinion of what constitutes an appropriate low and high cut-off threshold for PVD [2-4]. PVD remains under-recognized and under-treated in primary care practice, perhaps associated with current clinical tests. This typically consists of whether intermittent claudication is present or a monofilament test for sensory loss is conducted, both having low sensitivity. Hand held Doppler to determine the ABPI is currently the most accurate, noninvasive tool for the identification of PVD [5-7]. The normal ABPI range is between 0.9 and 1.2 with values below 0.5 indicating severe ischemia. Correlations between ABPI and HRV have been reported for patients with cardiovascular disease [8]. In asymptomatic individuals with reduced ABPI but above 0.8, vascular pathology is already present as indicated by increased oxidative stress [9, 10]. However conclusive results for a correlation between ABPI and HRV have not been reported.

A recently established multivariate data-driven approach clarified the relationship between PVD and cardiac autonomic dysfunction. The approach is based on the concept of decision guidance, which aims to direct decision makers towards rational outcomes in complex environments exploiting the richness of dynamic accumulation of data [11].

2. Method

Eight hundred and sixty eight individuals attended a rural screening clinic during 2002 to 2012. Of these, two hundred and thirty five individuals had their ABPI and HRV determined. ABPI was measured using a Welsh-Allyn automated blood pressure device for upper and lower limbs and the average of both left and right side was taken for our study. Three groups (ABPI<1.1; ABPI 1.1-1.2; ABPI>1.2) were divided based on values of ABPI. Twenty minute lead 3 ECGs were also recorded as well as age, gender, cholesterol and blood pressure. HRV was determined using time and frequency domain measures, and detrended fluctuation analysis (DFA). HRV results were divided into tertiles and the number of individuals falling within a ABPI group with the lowest tertile was analysed. Statistical analysis, carried out using Chi-square analysis was applied to identify significant differences between numbers of individuals between the ABPI groups ($p < 0.05$).

2.1. Multivariate data-driven approach

A data warehouse underlies the said multivariate data-driven approach. It is the intermediary link between conventional data stores and decision support techniques. The dimensional model is the conceptual basis for data warehouse development. Dimensional model design is essentially a denormalization technique that provides an intuitive view of data corresponding to the main areas of interest of the problem space [12]. It is commonly represented as a subject-oriented structure composed of fact tables and dimensional tables. Fact tables contains keys and numerical measures that can be summarized in terms of dimensions. In the clinical context, a dimensional model provides specific subject-oriented views on the patient records enabling multivariate analysis. and potentially leads to the realization of new associations between personal health status, intervention and individual outcome that also reflect a wider population use (Figure 1).

It is useful to note the use of a Cardinality dimension to distinguish between multiple clinic visits by the same patient. This dimension introduces a base level of temporal abstraction that is essential for clinical decision making [13].

Discretization is also essential for clinical decision making. Numeric clinical measures are continuous (real) by nature [14]. For aggregation and analysis that supports decision guidance these measures need to be converted to discrete values or ranges. In most circumstances the discretization criteria is determined by clinicians.

After the data was discretized, transformed and loaded into the warehouse it was possible to generate queries that can determine correlations between the ABPI measures and the HRV measures.

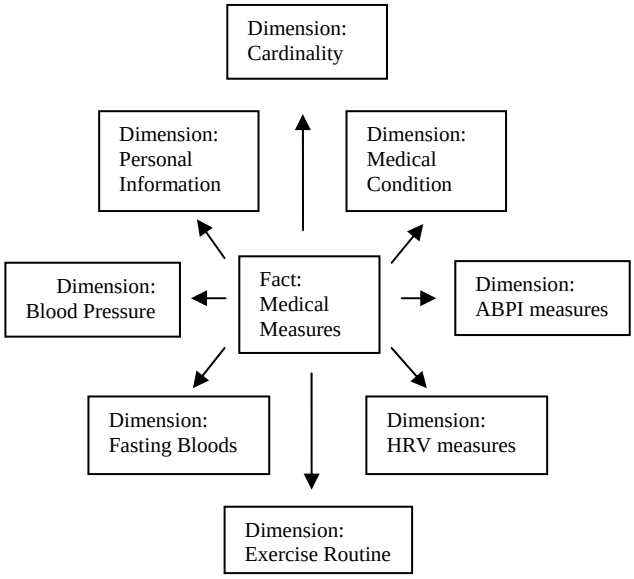

Figure 1. Dimensional model of the data warehouse

3. Results

Table 1. Demographics of participants.

Feature	Mean ± SD
Age (yrs)	56.7 ± 13.8
Gender	30 M, 40 F
*SBP	129 ± 16
DPB	78 ± 9
HDL	0.57 ± 0.78
LDL	1.09 ± 1.60

*SBP-systolic blood pressure; DBP-diastolic blood pressure; HDL-high density lipoprotein cholesterol; LDL-low density lipoprotein cholesterol

Demographics indicated a slight increase in systolic blood pressure with normal diastolic blood pressure. Both HDL and LDL were within normal limits.

Table 2. Chi square test results for HRV features.

Feature	p value
*LF(ms^2)	0.05
HF(ms^2)	0.02
SDNN(msec)	0.05
DFAalpha1	0.05

*LF-low frequency; HF-high frequency, SDNN-standard deviation of normalized beats; DFAalpha1-detrended fluctuation.

Figure 2 indicates the effect of a minor lowering or increasing ABPI from an ABPI between1.1 to 1.2. Both lowering and increasing led to significant change in the

HRV values associated with the time and frequency domain as well as nonlinear features including DFAalpha1.

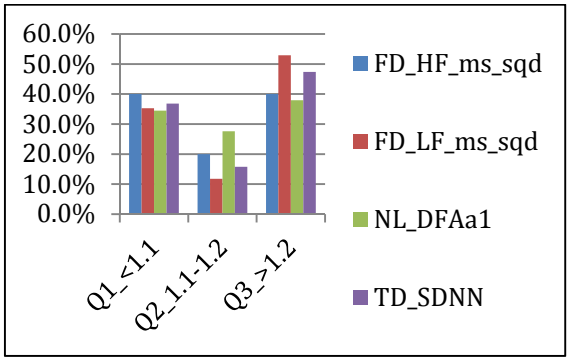

Figure 2. Changes in DFA feature distribution with changes in ABPI

Pearson's correlation analysis indicated a significant positive correlation for ABPI index between 1.1 to 1.2 ($p<0.05$). For lower and higher ABPI range there was a negative correlation but these were not significant (Figure 3).

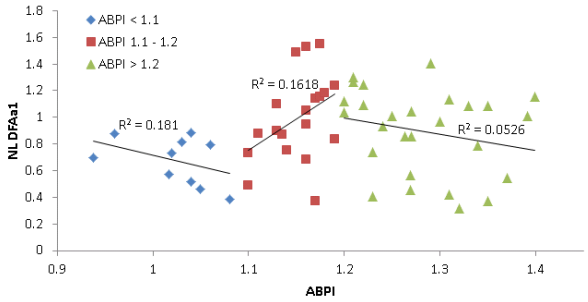

Figure 3. Pearson's correlation for ABPI intervals.

4. Discussion

Peripheral vascular disease has been shown to be associated with increased risk of morbidity and mortality in people with cardiovascular disease. The prevalence of peripheral arterial disease increases with age and is amounting to 10%–25% at age 55 years. Of those affected 70%–80% are asymptomatic [15]. Abnormal blood flow to the feet or peripheral neuropathy is known to increase the risk of ulceration [16]. Cardiovascular risk has been shown to correlate with measures of HRV [17]. HRV is the most often measured feature to indicate autonomic nervous system dysfunction as it is easily assessed [18]. The results indicate that as ABPI values move away from the 1.1 to 1.2 range, the HRV values fall. More individuals with lower HRV values are in the higher or lower ABPI groups suggesting that even small changes in ABPI may lead to changes in HRV that may be an early indicator of increased risk of arrhythmia or conversely that a drop in HRV may be associated with increased risk of PVD. In this study we show that a multivariate data-driven approach is useful to identify changes in ANS modulation of heart rate that is associated and related to peripheral vascular integrity. The multivariate data-driven warehousing approach identified changes in ANS function measured as HRV analysis that were not apparent with traditional analysis such as correlation analysis and can have further use in identifying complex associations between multiple factors.

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