A Novel Method to Detect Heart Beat Rate Using a Mobile Phone

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Abstract—**Heart Beat Rate calculation has traditionally been conducted using specialized hardware most commonly in the form of pulse oximeters or Electrocardiogram devices. Even though these methods offer high reliability, they require the users to have special sensor to measure their heart rate. In this paper we propose a system capable of estimating the heart beat rate using just a camera from a commercially available mobile phone. The advantage of this method is that the user does not need specialized hardware and s/he can take a measurement in virtually any place under almost any circumstances. Moreover the measurement provided can be used as a tool for health coaching applications or effective telecare services aimed in enhancing the user's well being.**

I. Introduction

THE rapid evolution of technology has brought highly sophisticated electronic devices like modern mobile phones in our daily lives. Smartphones with multimedia capabilities is such an example that opens up new possibilities for application development and service delivery. High speed processors, direct access to embedded multimedia hardware and internet connectivity provides the opportunity to interact with the user in a new and innovative way.

As the percentage of older people in the population of developed countries increases, there are more incidents of chronic disease that call for a higher percentage of the GDP to be spent on health care. Consequently, there is a call for technology to enhance the independence of the elder and allow more care services to be delivered at home [1].

Our work here is focused on utilizing a common device such as a mobile phone with a camera in order to calculate the heart beat rate which can later be used in personal health coaching applications or in telecare services. Our goal has been to demonstrate that such a measurement provides relatively good accuracy which can be enhanced further depending on the detection algorithm and the parameters used.

The research has been developed in collaboration with Health-Smart Limited that has substantial experience in self-care ICT for prevention and control of Long Term Conditions (LTC's) including cardiovascular and psychological conditions. One of their objectives is to empower patients to assess their state of body and mind and train them to improve their health and prevent LTC's by using inexpensive and friendly consumer ICT sensors [2].

Currently, there is an increasing research activity on wearable biosensor systems that often use a mobile phone or a PDA as a small scale processing and communications platform or as a media user interface unit. Studies have shown that when working with mobile phone and PDA's implementing healthcare systems, the vast majority of them use a mobile device for processing and user interface platform but not as a sensor itself [3].

In the study we can also observe that users tend to be very concerned with the way a sensor affects their appearance or habits, thus utilizing a device embedded sensor as a camera provides a truly non intrusive way of acquiring health information from the users without the need for them to train on how to use a new type of device provided they already feel comfortable enough using the menu of a mobile phone [3]. Moreover, the ease of use (simply placing one's finger on the camera) combined with the live feedback will likely be more appealing to the users and might play a positive role in engaging them to a process that could benefit their health; for example Health-Smart has developed breathing training applications that could help a patient practice breathing properly.

Common pulse oximeters are based on the different light-absorbing characteristics of oxyhemoglobin and deoxyhemoglobin at two different wavelengths (ie, 660 nm red and 940 nm infrared) and the pulsating nature of arterial blood flow [4]. With pulse oximeters, a finger or earlobe probe is used: a red light-emitting diode (LED) and an infrared LED are located on one side of the probe, and a photodetector is located on the other side [4].

The transmitted light is received by the photodetector and is divided into two components. Component A is transmitted light of variable intensity that occurs during a systole and is a function of the pulsations of oxygenated arterial blood. Component B is transmitted light that has a constant intensity and is a function of various tissues. The pulse oximeter divides the pulsatile absorption of component A by the background light absorption of component B, at the two different wavelengths, to obtain an absorption ratio and calculate oxyhemoglobin saturation often based on the Mendelson and Kent equation [5]

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II. METHODOLOGY

In order to extract the heart beat information from a stream of picture frames we need to deal with a number of problems in an efficient way. Live readings on a general purpose device such as a mobile phone complicates things further as we cannot control the lighting conditions nor the way the user is going to place his/her finger on the camera lens, an example is show below in Figure 1.

Figure 1: Example of using a smartphone for pulse reading

Our initial approach is to capture a given number of frames depending on the sampling rate of the available hardware and then analyse those trying to determine if our input matches the pattern of heart beating, or if the input suffers from high noise making it impossible to provide a reliable estimate. A sample is demonstrated in Figure 2, that displays Input data read from the camera while the user has his/her finger on it.

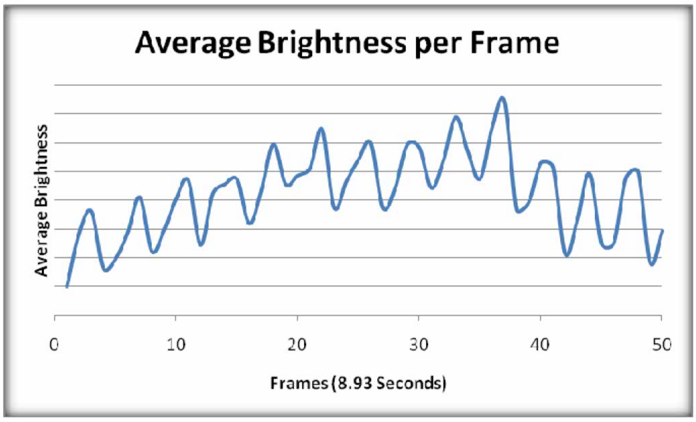

Figure 2: Camera Input Sample

The camera captures "real" time preview frames as the users place their fingers on the lens, then a grayscale portion of the image is scanned and processed resulting in brightness information for every individual frame. This way we can extract an average brightness value for every frame.

Every heart beat creates a wave of blood that reaches the capillaries in the tip of the finger: when the capillaries are full blood they will obstruct the light resulting in lower average brightness values. As blood is retracted more light can pass through – a change that is directly reflected on the increasing values of the brightness. This way we are able to capture the initial crude signal of the pulse and process it to extract information on the heart beat rate.

While normally taking a picture or a video require the camera to focus on an object, in our approach this is not necessary as the information we are interested in is contained within the brightness information of the pixels, therefore we deliberately set the camera properties to disable the option to focus.

The advantage of this application relies in its simplicity: the users only need to put their finger on the camera as in Figure 1 and then wait a few seconds to get a reading on their pulse However there are certain limitations related to lighting conditions which will be discussed later. Nevertheless, being able to calculate heart rate using a general purpose device such as a mobile phone opens up new possibilities for applications on health services and personal health coaching.

In order to ensure reliability on our readings we are matching our input signal to a crude heart beat pattern of alternating peaks and troughs. The algorithm is scanning a subset of the frames until it detects a peak, then it will attempt to detect a trough. When a predefined number of peaks – troughs have been detected we consider the algorithm to be synchronized as shown in Figure 3, from that point on we are able to calculate a good estimation on the beats per minute. During our tests we have been working with a wide rage of frame sets resulting in synchronization of five to ten or more pulses while matching local maximum and minimum pairs. It appears that a minimum of six to seven pulses gives good results in low noise / adequate lighting conditions, moreover mobile phones that come with a led-flash next to the camera as the one shown in Figure 1, can provide the necessary light in a dark environment, however our measurements were taken without the use of such additional light.

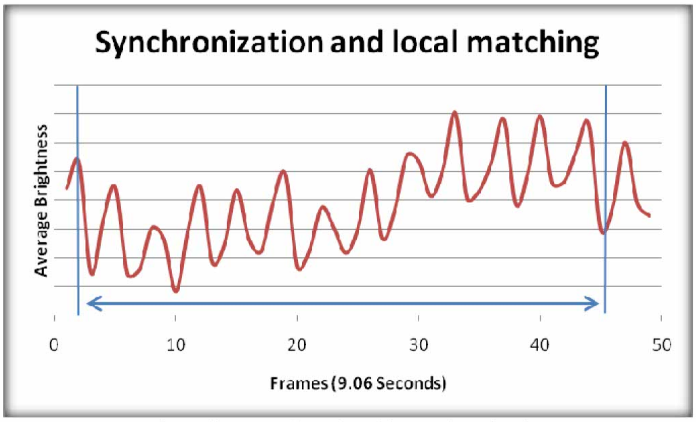

Figure 3: Input Sample with synchronization

Naturally, when dealing with a general purpose device and non laboratory conditions, for such a measurement one gets a good amount of noise that can influence the calculation, therefore we always use a certain noise margin in order to sort an actual peak from noise signals. A peak is defined as point x where f(x-1) + nm < f(x) > f (x+1) + nm. The discrete function f(x) is our brightness sample and nm is the desired noise margin.

Every average brightness value for each frame is extracted along with a timestamp of nanosecond resolution according to the operating system. This enables us to minimize the negative impact of the lag coming from the limited processing power of the device, ensuring that our estimation will be practically unaffected.

After successfully developing this application on the Symbian operating system [6] our research moved on experimenting with the Android platform using an HTC Tatoo running Android 1.6. One of the main differences is that Android adopts a higher level approach similar to Java while Symbian takes the developer closer to the hardware by using C++.

For this particular application it is desirable to access the hardware in a direct way thus minimizing the delay for acquiring frame previews and processing them without lagging the system. Even though Symbian would be most suitable for that cause, Android still provides adequate facilities to achieve a comparable result.

Unfortunately, the frame rate achieved under Android using our middle range hardware was only about 5 frames per second; a higher framerate would provide higher accuracy and reliability as our sample rate of 5 fps effectively limits the range of the beat rate we can estimate as suggested by the sampling theorem. The equivalent frame rate under Symbian, using Nokia N95 8GB was 25 fps.

The relatively low frame rate is mostly related to the hardware's processing capability and also to the camera's characteristics, but it's not limited to that as Android currently copies every preview frame to a new buffer before passing it to the programmer; this subsequently triggers a garbage collector call that will slow down the given device for 80-90 ms per frame. Nonetheless, more powerful hardware is expected to achieve higher framerates while Android is still under heavy development and optimization.

III. Results

We evaluated the algorithm against a commercially available pulse oximeter with given maximum error of 2 beats per minute. Samples were taken from a group of 50 people between 21 and 55 years old, with an average age of 31,3 years.

Table 1 summarizes the results for the samples taken in well lit areas, were the average light absorbed by the camera lens without any obstruction was 46% of the maximum amount of light that the lens could absorb. The users had to keep their finger steady and the first measurement was always discarded so that users would get to feel more comfortable with the device. Results were also discarded in cases where users said they were not comfortable with the placement of their finger. The algorithm will also filter out unreliable readings when there is excessive finger movement.

Fifty frame subsets were used for this set of results; that corresponds to an average of 8.9 Seconds per decision which only provides marginal accuracy, however the algorithm was fine tuned up to the point that it would consistently estimate Beats per Minute (BpM) with over 91% accuracy. Moreover, there is an inherent 2 BpM maximum error for the pulse oximeter we used to check our precision. The average error for this scenario was at 4.13% with a maximum of 8.11% and a minimum of 1.49%.

Due to our synchronization window we have achieved very good resolution. Pulses are identified and nanosecond resolution timestamps are acquired from Android while the application is running. Therefore the greatest risk for inaccurate results remains to be the user, low light and low performance hardware.

Table 1: Well Lit Area Sample

Estimated BpM	Measured BpM	Relative Accuracy	Relative Error
65	66	98.46%	1.54%
63	67	93.65%	6.35%
73	70	95.89%	4.11%
71	68	95.77%	4.23%
68	70	97.06%	2.94%
67	68	98.51%	1.49%
68	71	95.59%	4.41%
75	72	96.00%	4.00%
76	73	96.05%	3.95%
74	68	91.89%	8.11%
73	71	97.26%	2.74%
68	71	95.59%	4.41%
75	72	96.00%	4.00%
72	77	93.06%	6.94%
75	73	97.33%	2.67%

In the next set of samples we tried to assess the importance of lightning conditions to the system. The average light absorbed by the camera in this case was 13 % of the maximum amount of light the lens could absorb. The same protocol was followed.

The results presented in Table 2 demonstrate how this approach is tolerant to relatively low lighting conditions. The average error was 4.67%, a value very close to that of our previous set of samples, while the lowest relative accuracy observed was 89.87% and the lowest relative error was 1.28%.

The sample time of 50 frames proved to be quite efficient as it requires the user to stand still for roughly 9 seconds, which proved to be acceptable. Larger frame sets were more prone to errors as it is hard for the users not to move at all for e.g. 75 frames that take 14.7 Seconds. Smaller frame sets were found to be more inaccurate due to the small amount of samples the system can scan in a time window of less than 9 seconds.

Table 2: Average Lit Area Sample

Estimated BpM	Measured BpM	Relative Accuracy	Relative Error
74	78	94.87%	5.13%
76	78	97.44%	2.56%
77	78	98.72%	1.28%
71	77	92.21%	7.79%
71	79	89.87%	10.13%
81	79	97.47%	2.53%
83	84	98.81%	1.19%
83	82	98.78%	1.22%
79	75	94.67%	5.33%
82	76	92.11%	7.89%
76	78	97.44%	2.56%
86	82	95.12%	4.88%
77	78	98.72%	1.28%
73	67	91.04%	8.96%
74	69	92.75%	7.25%

IV. Discussion and Conclusion

This application is a subsystem of a telecare platform that is being developed in collaboration with our industrial partner Health-Smart Limited who has filed a patent [8] for this application, retaining the full intellectual property of this project.

In this work we demonstrated the proof of concept and the potential of the algorithm and the platform as a tool for health care delivery.

The research demonstrates a cheap and effective way of calculating the Heart Beat Rate using commercially available Smartphones. The system was successfully designed and tested using the Symbian OS and is now being extended to other OS's including Android 1.x/2.x and Windows Mobile, our current hardware cost on this system did not exceed 300£.

Our findings were very encouraging considering that the algorithm is not yet fully optimized up to the extent we plan to, and we are waiting for new hardware to be available in order to improve the accuracy and resolution. Our forecast is that in the near future we will see commercially available applications that will use a mobile camera as a sensor and innovative software that could use this input in order to provide health enhancing services to the users.

Higher sampling rates would not only improve accuracy, but also it could potentially shorten the sampling time for the user, making the application easier to use and less prone to errors from excessive movement.

Moreover, we have not exhausted our approach on adaptive calculation estimates; the project is still in development and one of the possible next steps will be to use adaptive techniques for real time feedback in personal health coaching applications like using the data from this application to drive an interactive multimedia software that would aim on reducing a person's blood pressure; all in the same device. The same adaptive technique can be used in order to dynamically estimate the noise levels and set the noise threshold accordingly; this will subsequently result in more accurate measurements in lower light conditions.

As Shnayder et al. denote in [7], life expectancy is constantly increasing over the last decades, so does the burden on the health system supporting people with chronic conditions. The only way out of this is implementing telecare solutions that will manage to increase the quality of delivered health care while maintaining low installation and running costs.

Health services delivery is about to change, but it is the nature of the service itself that will gradually shift from re-active treatment of conditions to pre-emptive health care: avoiding health risks can be more efficient than sustaining patients with chronic conditions that could have been avoided [2]. This is where health monitoring and cognitive therapy comes to offer new possibilities, to provide the users with information on how to avoid getting a health condition rather than focusing on how to treat it.

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