Karlsruhe Institute of Technology

Non-Invasive Blood Glucose Monitoring in Ears

Seminar Paper

by

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Abstract

TODO

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1 Introduction (chapter)

1.1 Motivation

Diabetes is common. Approximately 37.3 million people in the United States have diabetes, which is about 11% of the population. Type 2 diabetes is the most common form, representing 90% to 95% of all diabetes cases. About 537 million adults across the world have diabetes. Experts predict this number will rise to 643 million by 2030 and 783 million by 2045.[1]

1.2 Goal and Scope of This Paper

2 Background: Diabetes and Blood Glucose Monitoring

2.1 Medical Context

Diabetes mellitus (I will be referring to it as diabetes but diebetes mellitus is the medical term) is a metabolic disease, involving inappropriately elevated blood glucose levels (hyperglycemia).[19] It can lead to severe complications, such as cardiovascular disease, kidney damage, nerve damage, eye and oral complications.[4] Diabetes can also develop when the body of a person isn't responding to the effects of insulin properly. Diabetes affects people of all ages and most forms of diabetes are chronic.

The most common types of diabetes are Type 2, Prediabetes, Type 1 and Gestational Diabetes. The most common of these is Type 2 Diabetes. This is the type where the body doesn't respond to insulin poperly or the body doesn't produce enough insulin. It is possible though that both is true for a person. Prediabetes is a condition where blood glucose levels are higher than usual, but not as high as to be diagnosed with Type 2 diabetes.[1] Type 1 diabetes on the other hand is an autoimmune disease, which is a malfunction of the body's immune system that causes the body to attack its own tissues.[1,9] In this case the immune system attacks insulin producing cells in the pancreas with up to 10% of people having diabetes, having Type 1 diabetes. Another form being Gestational diabetes that develops and usually goes away during pregnancy. But people that had Gestational diabetes are at a greater risk of developing Type 2 diabetes later in life.[1]

2.2 Traditional invasive measurement techniques

When left unmanaged and untreated, diabetes causes serious health problems, as discribed earlier. So it is crucial to manage diabetes where monitoring blood glucose levels is essential. Current/-traditional techniques to measure blood glucose levels are invasive. The most common method to measure the blood glucose level is with a glucose meter, or glucometer. This is a small and portable machine that can measure a person's blood glucose level, requiring only a small sample of blood. There are multiple ways to collect the blood sample but the most common one is to prick the finger with a small needle. Other test sites are the upper arm, forearm, base of the thumb or the thigh. But readings in the fingertip are much more accurate so preferred.[8]

Another method is continuous glucose monitoring where how the name already suggests the glucose levels are monitored constantly. The sensor for the monitoring is either inserted under the skin (a small needle) and held in place with a stick patch (disposable sensor) or it is placed fully under the skin (implantable sensor). These sensors then transmit the data to a reciever, which more often is a mobile phone. There a person can see its glucose levels, trends and get alarms, if the blood glucose level is too low or high.[21]

2.3 Need for non-invasive approaches

While continuous glucose monitoring (CGM) offers significant advantages over periodic finger-prick testing, such as enabling easier management of blood glucose levels and reducing the incidence of acute glycemic emergencies, the invasive nature of traditional methods remains a barrier to widespread and sustained use. Disposable CGM sensors must typically be replaced every 7 to 14 days, and implantable variants can last up to 180 days.[21]

However, these conventional and minimally invasive methods are often painful, can be costly, and may discourage consistent monitoring, leading to poor adherence to testing routines[14]. By contrast, non-invasive glucose monitoring approaches hold promise for daily and continuous use by being painless, more comfortable, and potentially less costly.

Such innovations could significantly improve patient compliance and quality of life, addressing the limitations of traditional monitoring modalities.[10,17] Ultimately, non-invasive technologies may deliver effective, user-friendly alternatives that facilitate better long-term management of diabetes.

3 Photoplethysmography

3.1 Physical principle

Photoplethysmography (PPG) is an optical technique that measures blood-volume changes. PPG utilizes optical sensors to detect these changes by emitting light into the skin and measuring the amount of light absorbed or reflected by blood vessels. Depending on the energy of incident photons, bond deformation or vibration at different energy level of different bonds occurs. So, only the photon with energy that corresponds to the difference between two of its energy levels can be absorbed.[5,7] Glucose absorbs light at the fundamental frequencies (2–2.5 μm) and first overtone region (1.53–1.82 μm). These wavelengths have the drawbacks of needing expensive sensors, strong absorption due to water and scattering of fatty tissue. For the second overtone region (0.8-1.6 μm) on the other hand, way cheaper infrared sensors can be used. The absorbance of glucose is much weaker compared to the previously mentioned wavelengths, but still detectable compared to other tissue chromophores.[12]

3.2 Transmission vs. reflection method

There are two implementation for PPG:

Transmission PPG places the light source on one side of a thin body part (e.g., fingertip or earlobe) and the photodetector on the opposite side. This way the light traverses the tissue. This method usually yields a higher amplitude and cleaner waveforms. The drawback is that it requires thin, well-perfused bodyparts and is sensitive to local perfusion changes (e.g., cold-induced vasoconstriction).[7]

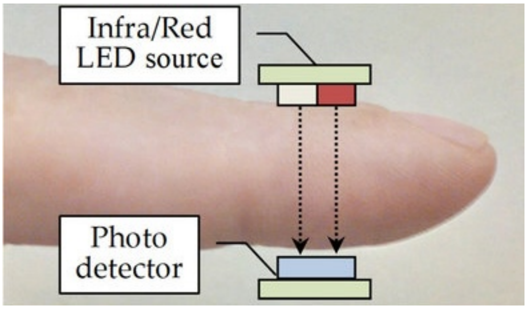

Figure 3.1: Transmission PPG on a finger

Reflection PPG places the light source and photodetector on the same side. The light enters, scatters within the tissue, and a portion of it returns to the photodetector. While the amplitude is often lower and more prone to motion artifact than transmission PPG, reflection PPG works on most body sites.[5,7]

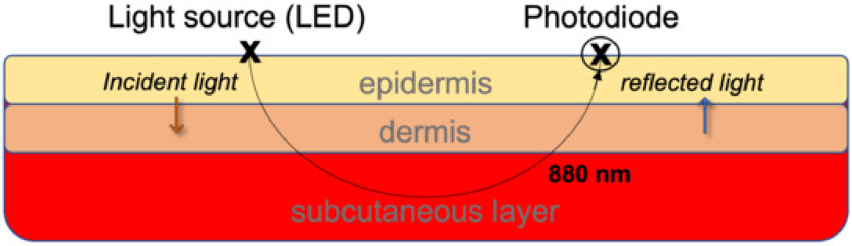

Figure 3.2: Reflection PPG principle

3.3 Signal characteristics and challenges

Physiological content. The PPG signal carries a mix of information. The pulsatile part (AC) reflects stroke volume, arterial stiffness, and wave reflections, which can be seen in its amplitude, rise time, and the shape of the dicrotic notch. Breathing introduces slower variations in the baseline. Taking the second derivative of the PPG makes the inflection points more visible and allows the calculation of indices linked to vascular aging and stiffness.[5,7]

Artifacts and confounders. Several factors can distort the signal: Movement of the sensor or tissue can change how light passes through which creates motion artifacts. Stray ambient light may leak into the sensor. Blood flow at the measurement site can also vary with temperature or autonomic activity. For example, vasoconstriction can reduce or even eliminate the signal at extremeties. The amount of pressure from the device itself matters too, since it alters local blood volume. Peripheral sites are the most affected when perfusion is low, while the ear canal has shown stable signals with fewer dropouts, even during induced vasoconstriction or in surgical conditions.[6,20] To improve signal quality, common steps include subtracting ambient light, adaptive filtering, using motion references for regression, robust peak detection, and applying quality checks before extracting features or feeding the data into models.[5,7]

Implications for body-site choice. Where the sensor is placed strongly affects performance. Transmission PPG usually produces higher amplitudes and cleaner signals but often fail during cold-induced vasoconstriction. Reflection PPG setups can be used at most body sites, but they typically have lower amplitude and are more sensitive to motion.[5–7,20]

4 Anatomical zones for measurement

4.1 Anatomical zones overview

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Conference contributions

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