A Multimodal Sensing Platform for Cyclist Risk Perception in Urban Scenarios

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***Abstract*—Cycling is increasing as an urban activity, but the cities are not following this growth at the same rate. More bike lanes and bike infrastructures must be built in order to accommodate this rising culture. We know very little about the stress and the conditions cyclists are put through in their daily journeys. The main focus of this work was to develop an App and a method that could show how the smartphones can be used to study this increasing activity. As these devices are getting more popular and due to the fact that these devices are equipped with several sensors, such as gyroscopes, accelerometer's, GPS receivers and good cameras, they become the perfect candidates for this job.**

***Index Terms*—Cyclist, optical-flow, traffic, HRV, Smartphone, Stress.**

I. Introduction

CYCLING is increasing as an urban activity, with more people choosing the bicycle as a mean of transportation. In Europe there are 2 bicycle sold for each car sold. In the year of 2011 just in the E.U. zone, 20 million bicycles were sold [1]. This increase of cyclists has led to a bigger number of bike related accidents [2].

To accommodate this bigger number of cyclist, studies have to been done in order to help making the cities more bike friendly. Most of the studies related to this problem were done based on surveys and empirical calculations where the level of comfort for the urban cyclist was based on known variables such as: speed limit, level of traffic, presence of a bike lane and road width [3]. More recently an MIT project used a bike helmet with an EEG sensor that could map the city streets based on the brain waves [4].

This work aims to show that the smartphones can be used as a tool to study the urban cyclist. Smartphones are at the same time cheap and easy to implement in large scale. So cyclists with a smartphone can evaluate several aspects of "the state of the city".

This work has three main parts:

- Data acquisition in real-time
- Data processing offline
- Data result analysis

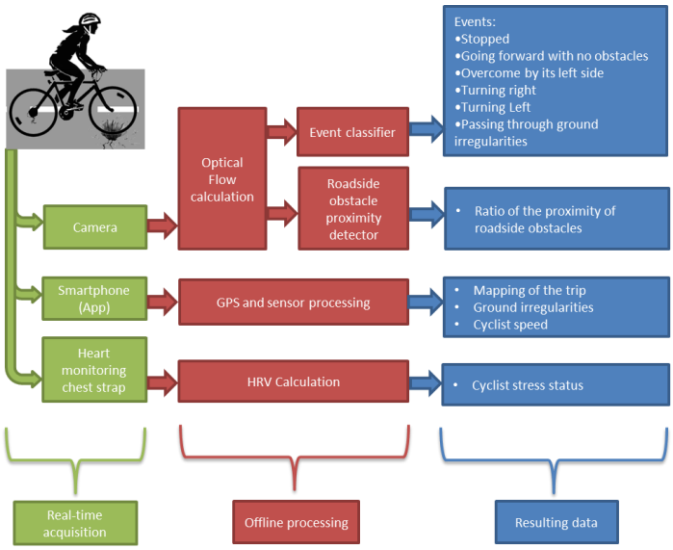

Figure 1 – Flowchart of the system architecture.

II. Sensing platform

The goal of this work is to create a study tool using a smartphone; however in the tests performed during this thesis, an action cam was used instead of the smartphone camera. This was due to the fact that the smartphone bike mount used wasn't rigid enough, resulting in a very sluggish video footage with rolling shutter artifacts, this problem can be overcome using a better bike mount.

So to study this problem we used three main components:

-Smartphone
-Action Cam (to replace Smartphone Camera)
-Heart monitoring chest strap

A. *Smartphone.*

Smartphones are becoming cheaper and more abundant nowadays. For that reason they were chosen to record the GPS coordinates, as well as the gyroscope and accelerometer values.

The smartphone was mounted on the bike handle.

1) Android App – Bike Monitor

In order to record the values from the smartphone sensors, an Android App was developed named "Bike Monitor". This app records the following data:

- GPS coordinates;
- Acceleration on the 3 axis (Accelerometer);
- Rotation on the 3 axis (Gyroscope);
- Time date, and
- Video (Camera).

B. Action Cam.

As previously mentioned an action cam was used to capture video footage instead of the smartphone camera. This alternative was used because these type of camera are designed to be used under heavy oscillating environments and have designed mounts for that purpose, resulting in cleaner and nicer videos.

The action cam was mounted on the front part of the bicycle frame.

C. Heart monitoring chest strap

There are several physiological responses to stress. One simple way to detect stress is by calculating the Heart Rate Variability, often referred as HRV. The HRV can be calculated from an ECG signal. To record that signal an heart monitoring chest strap was used.

The chest strap was chosen because it's cheap, simple and comfortable to use in contrast to more complex and pricier systems.

III. EVENT DETECTION BY VISUAL MOTION ANALYSIS AND EGO-MOTION SENSORS

A. Image Processing.

In order to identify the surrounding events of the urban cyclist, a camera was used to capture video footage. The captured images should identify stressful situations, for instance the cyclist being overcome from its left in a close call or the presence of ground irregularities.

With the captured images it was possible to calculated the optical flow. Then a descriptor was built around this calculation and a k-NN Nearest Neighbor classifier was built.

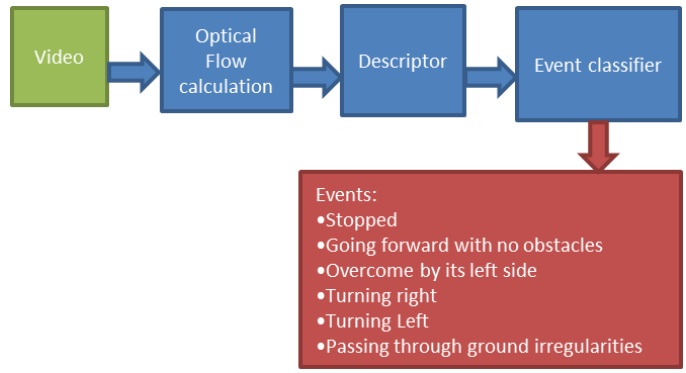

Figure 2 – Flowchart of the image processing.

1) Optical flow calculation

The optical flow gives us information about the movement pattern between two images. In this work this movement patterns were studied in order to classify known events.

The optical flow of the captured images was calculated using the Lukas-Kanade algorithm. This method was chosen because it was easy to implement and had fast processing times.

Each frame of the captured video had a lot of unnecessary information, for that reason the focus was put on the bottom part of the image (figure 3).

Figure 3 – Frame with marked analysis window.

This part of the image was chosen because it's where all the traffic and obstacles are located.

For calculating the optical flow, instead of using a "good features to track" algorithm like Shi-Tomasi, a window of evenly spaced points was used instead. This approach allowed us to increase the number of points to be processed.

However this approach doesn't detect the best points to be processed, which results in an optical flow with many errors. To overcome this problem a different approach for detecting outliers was used. Instead of processing the optical flow

between two frames, the optical flow was processed between three frames as it (figure 4).

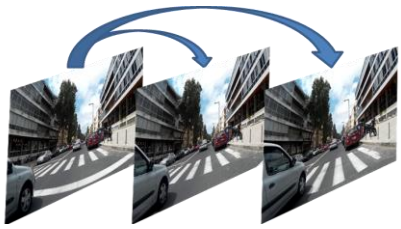

Figure 4 – Approach used for the calculation of the optical flow

This approach returns two flow vectors instead of one. Then if the angle between the two resulting vectors is very big, the corresponding point is considered an outlier.

2) Descriptor

In order to analyze the processed optical flow, the window selected was divided into 6 evenly spaced rectangles as shown in figure 5.

Figure 5 – Frame with the 6 evenly spaced rectangles.

Given this division, it was calculated for each rectangle an histogram of the flow vectors direction, with 8 evenly divided bins from [0 ; 2π]

The mean size of the vectors of each rectangle was also calculate.

3) Event classifier

With the defined descriptor, an event classifier based on the k-NN Nearest Neighbor was built with the following event classes:

- Cyclist stopped;
- Cyclist going forward with no obstacles;
- Cyclist being overcome by its left side;
- Cyclist turning right;
- Cyclist turning left, and
- Cyclist passing through ground irregularities.

This classifier consists of a bank of 100 images with known situations, with the exception of "Cyclist standing still".

The classification is given based on the k-NN Nearest Neighbor algorithm, were the histograms of the bank are compared with the histograms of the image to be classified. The nearest top 10 images determine the category of the image to be classified.

The class "Cyclist standing still", is determined based on the calculated mean size of the vectors. If the mean size of the vectors is small, than the image is classified as "Cyclist standing still".

4) Roadside obstacle proximity detector

The cyclists usually ride on rightmost side of right lane, for that reason they are very close to the road side. An obstruction or obstacle on the roadside can lead to a stressful situation. For that reason a roadside obstacle proximity detector was built.

This detector works by analyzing the average size of the vectors from the third rectangle in relation to the average size of the vectors form the entire image. If the average size of the vectors from the third rectangle is bigger than the average size of the vectors from the entire image, then there must be an obstruction or obstacle in the roadside.

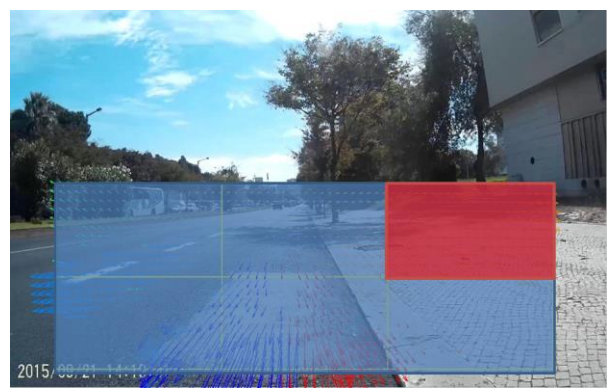

Figure 6 – Analysis window with marked rectangle used on the roadside obstacle proximity detector.

To measure the obstruction proximity, a ratio between the average sizes of the vectors from third rectangle over the average size of the vectors form all the image was calculated.

B. Accelerometer Processing

Cyclists must be extra cautious when driving in damaged roads or in ground irregularities. For this reason a ground irregularities detector was build.

As previously mentioned the smartphone was mounted on the bike handle and with this setup it is possible to detect ground irregularities.

As the biker passes through an irregularity on the road, the accelerometer sensor of the smartphone registers the acceleration value (figure 7).

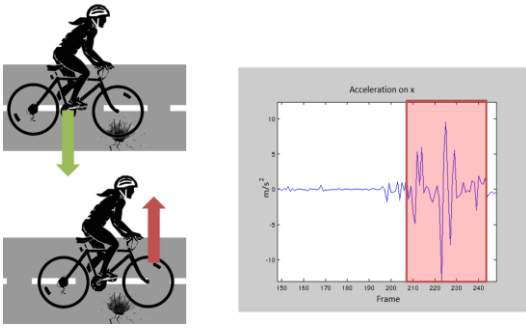

Figure 7 – Ground irregularities detector scheme.

This oscillation after being detected is registered as a ground irregularity.

IV. Stress detection by HRV

In order to validate the stressful events identified along this work, a stress detector was developed.

Studies have shown that there is a relation between the variation of heart Inter-beat Intervals (RR) and the level of stress of a person [5]. This variation is called Heart Rate Variability commonly known as HRV.

There are several ways to calculate HRV. In this work a frequency domain method was used. This method was chosen because it requires a smaller time sample to perform the analysis, in contrast to time domain methods [6].

In this method the Power Spectral density (PSD) of the RR intervals is calculated.

From the resulting PSD we know that:

- Low Frequencies (LF): 0,04 Hz a 0,15 Hz – correspond to the sympathetic stimulation (Stress) [7].

- High frequencies (HF): 0,15 Hz a 0,4 Hz – correspond to the parasympathetic stimulation (Relaxed) [7].

To determine the stress conditions of the cyclist the LF/HF ratio was calculated as followed:

Let RR(t) be the variation of RR values along time t and $S_{RR}(f)$ the power spectral of RR(t)

$$\frac{LF}{HF} = \frac{\int_{0.05}^{0.15} S_{RR}(f)df}{\int_{0.15}^{0.4} S_{RR}(f)df}$$

Summing up, higher values of the LF/HF ratio relate to a more stressful event.

There are no guidelines regarding the normal values for the LF/HF ratio as it changes from person to person based on their age, weight, height, and cardiac health [7], [8]. For this reason, the variation of the LF/HF ratio must be analyzed instead of the exact value.

One limitation of this method is that in exercise sessions there is an increase on the sympathetic stimulation, resulting in an increase in the LF/HF ratio. However after the stabilization of VO2 value (Oxygen consumption), this stimulation decreases, returning to normal values [6]. This aspect must be taken into account when analyzing the LF/HF ratio values.

V. Experiment testing in real scenarios

The presented method was tested several times. In total 10 tests trips were performed, 8 of them in Lisbon city and 2 in Ponta Delgada city. A database was created based on this test trips, containing around 2h00 of data with the following data properly synced:

- GPS coordinates
- Video
- Electrocardiographic record (ECG)
- Acceleration on the 3 axis (Accelerometer)
- Rotation on the 3 axis (Gyroscope)

In this chapter, the results of one of the test trips will be analyzed. This example took place between Instituto Superior Técnico and Rua Pardal Monteiro on the September 14 of 2015 around 2pm.

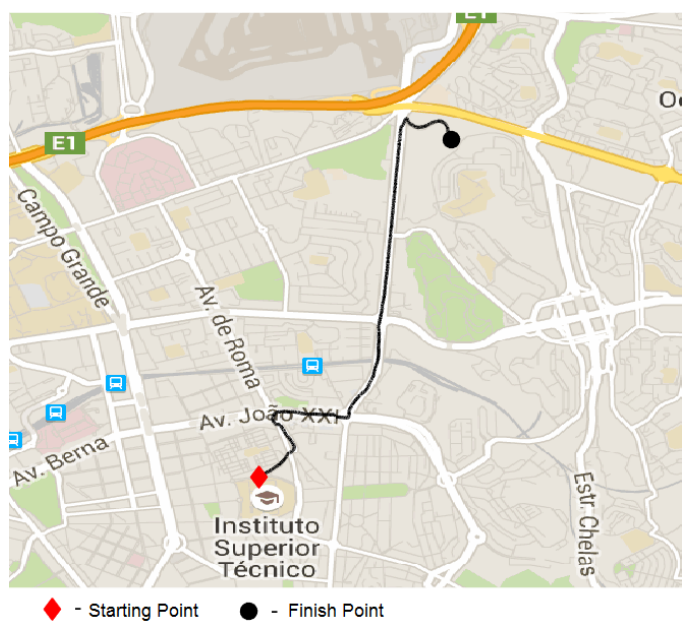

Figure 8 – Map of the cyclist path.

Several variables were extracted from the data collected and will be presented only the ones that have the most interest.

1) Stressful events found

In this test trip it was possible to identify a high LF/HF road section, corresponding to a climb, which was a known limitation of the system. In fact, the climb forces the cyclist to exercise more and it leads to myocardial stress. However the system detected two zones that were not climbs but had high LF/HF ratio. This zones are marked in figure 9.

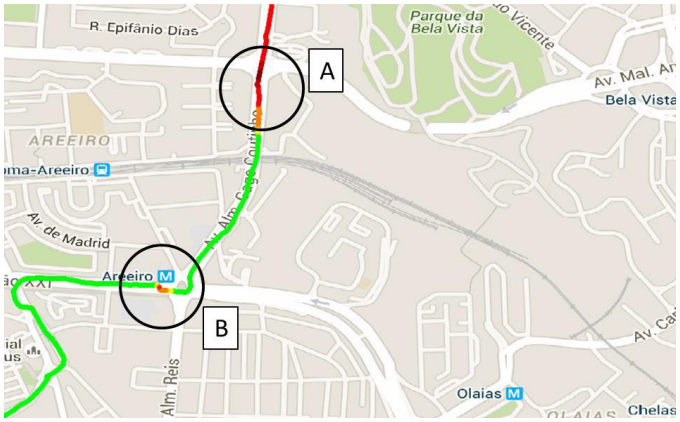

Figure 9 – Map with high LF/HF zones marked.

Analyzing the images referring to point A, the cyclist had a close call from overcoming car by his left (figure 10). This close call could be directly related to the rise in sympathetic stimulation.

Figure 10 – Images corresponding to marker A – Close call overcome by the cyclist left.

In point B, after the images analysis, it was found that the Rotunda do Areeiro had a lot of traffic at that specific time, which was a possible reason for the rise of the LF/HF ratio (figure 11).

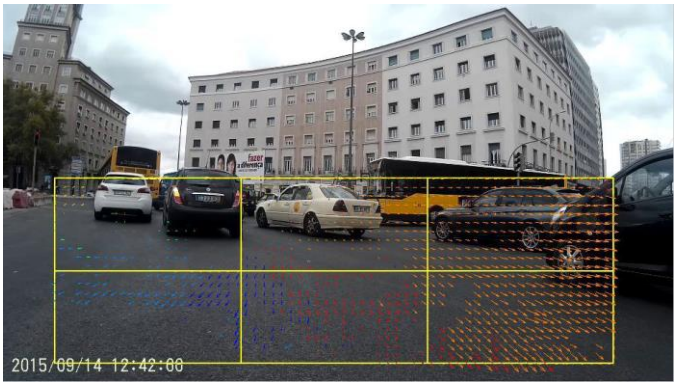

Figure 11 – Image corresponding to marker B – traffic in rotunda do Areeiro.

VI. CONCLUSIONS

With this work it was possible to prove that today smartphones can in fact be used as tools to study urban cyclists, identifying stressful city sections.

It was also proven that the analysis of the optical flow can be a good way to identify several stressful events in an urban bicycle journey.

Although the HRV analysis is a powerful and easy tool to implement, it's not the most adequate way to measure stress while cycling, due to the fact that it is affected by physical exercise. Other alternatives should be studied.

A. Future work

After being proven that the smartphones can in fact be used as cyclist monitoring devices, it would be interesting to implement the developed app and method in a large number of cyclists, in order to get a significant data sample. This large amount of data should then be studied to help making the cities more bike friendly.

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