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Institute for Systems and Robotics | LISBOA

A Context Aware and Video-Based Risk Descriptor for Cyclists

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ISR LISBOA / LARSyS

Bicycle

Smartphone

Download our Android app

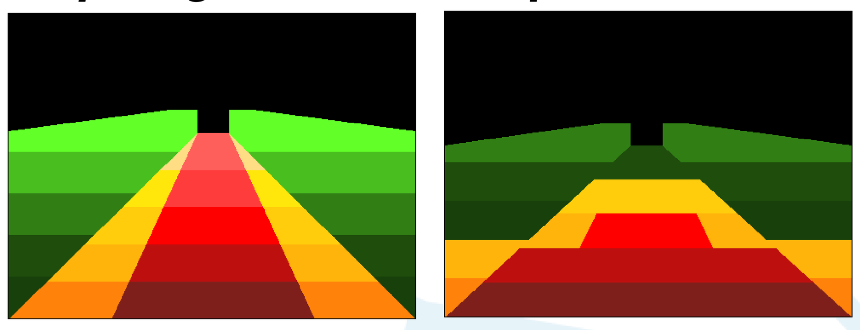
Risk Descriptor

IMAGE-BASED RISK ASSESSMENT

1) Estimating the Focus of Expansion

Combining the **optical flow** and **object detection** in the captured video we estimate the cyclist's motion by discovering the **Focus of Expansion (FOE)**.

2) Computing the Risk Descriptor

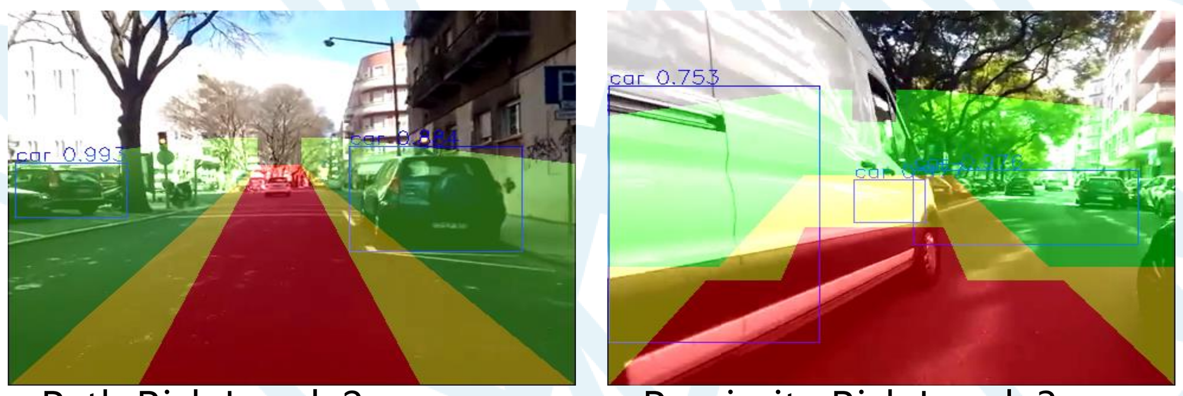


With the discovered FOE we divide the image into **25 regions** that map the **cyclist path** and the **proximity** to the cyclist. The **risk descriptor** maps the **perception of risk in each** one of these **regions**.

The risk factor in each region is computed by taking into account the **location and type of objects** in that region and the **region risk level** (red is riskier than yellow, which is riskier than green).

3) Evaluation of the risk perception by computing the distance metric for the descriptor

To **find the risk factor** of a new instance we **compare the risk descriptor** of a test image with a set of **manually classified images**. The risk assessment is performed using **two metrics: Path Occupation and Proximity**. The classification is divided in **3 risk levels** for each metric.



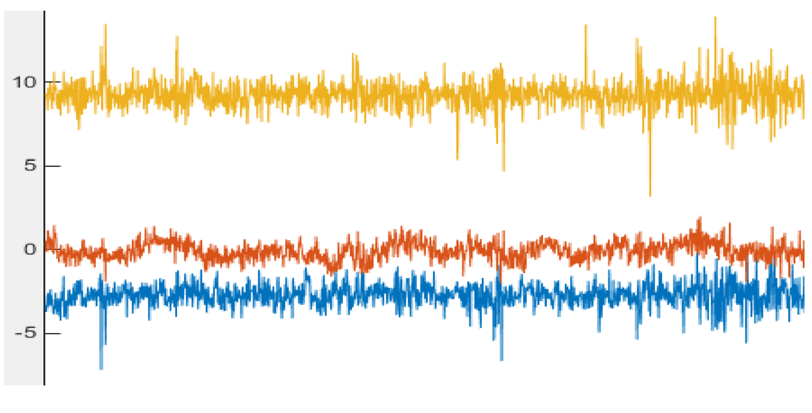
Path Risk Level: 2

Proximity Risk Level: 3

BEHAVIOUR ANALYSIS

1) Data Acquisition and Pre-processing

Linear acceleration, gyroscope and GPS data given by the smartphone.



2) Feature Extraction

We extract **54 features** from the signals such as:

- GPS speed signal;
- time and frequency domain features from the 3-axes acceleration and gyroscope;
- time domain features of the acceleration cross correlation between pairs of axes.

3) Classification Method – SVM

We use **Support Vector Machines** (SVMs) in a OVA (One-Vs-All) approach with Kernels to **classify human activity** into **three classes: cycling, walking and riding a motorized transport** (e.g. a car or a bus).

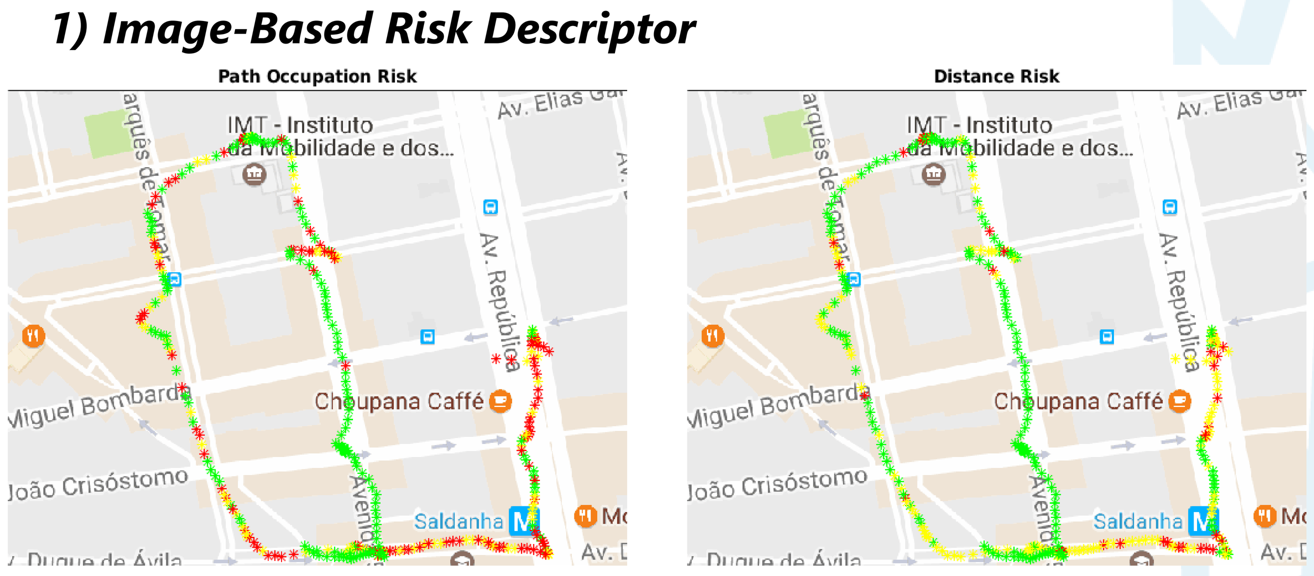
4) Adding Temporal Continuity and Feature Selection

SVMs are effective in classifying individual frames but they do not account for temporal continuity. We **introduce temporal continuity** exploring the idea that probability values computed for a frame can benefit the classification of successive temporally close frames.

Additionally by **applying Recursive Feature Elimination** (RFE) to our SVM classifier we are able to **significantly reduce the dimensionality** of our problem.

EXPERIMENTAL RESULTS

1) Image-Based Risk Descriptor

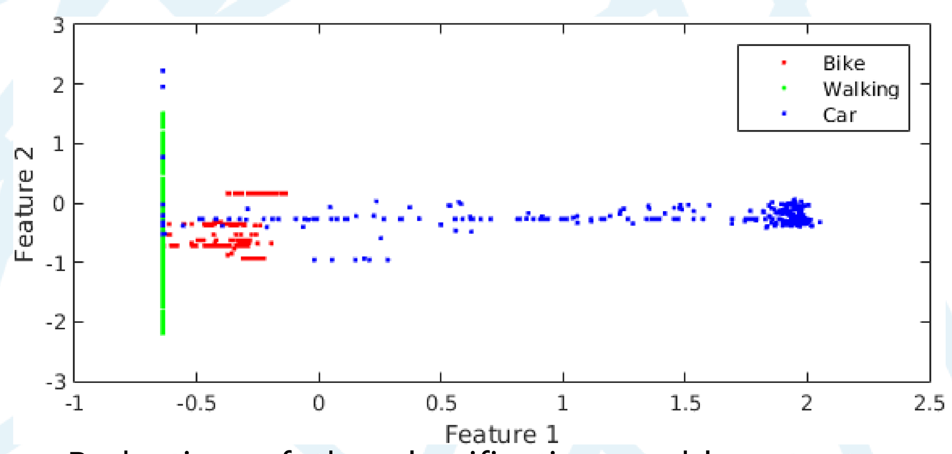


Geo-referenced risk perception levels.

2) Behaviour Analysis

SVM classifier achieves **≈ 99% accuracy** for a linear kernel.

Applying **feature selection**, we move from **≈ 99%** accuracy when **including all 54 features** to **≈ 94%** after reducing the **dimension of the data to 8**. This is a very promising result, since we can **significantly lower the computational load** at the cost of a **slight accuracy reduction**.



Reduction of the classification problem to two dimensions, showing the separation among the 3 classes.

FCT Fundação para a Ciência e a Tecnologia
MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E ENSINO SUPERIOR

Project: UID/EEA/50009/2013

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