Predictive Modeling of risk factors in slaughterhouses using Low-cost inertial sensors

Thesis Defense

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Outline

Section 1

Slaughterhouses, Wearable Technology and WRMSDs

Motivation

Challenges in the Meat Processing Industry

1. Labour represents a large percentage of the costs.
2. Global economic volatility induces pressure in manufacturing operations, specially when automatization is not yet possible.
3. Larger demographic processes will constrain labour markets in the future.
4. Individual health is often overlooked by decision makers.
5. Fatigue and bad practices in manual activities induce social and economic pressures.
6. Work-Related Muscukuloskeletal Disorders (WRMSDs) are the leading cause of work disability, sickness and absence from work [Bevan, 2015].

Motivation

State of the IoT Industry

1. IoT market has grown dramatically in the last five years.
2. Intelligent systems seem possible at the fusion between IoT and AI.
3. IoT market share by sector shows that wearable technology still represent a small proportion of the total (3%).

Motivation

Wearable Technology

1. Wearable devices have been used successfully in Human Activity Recognition (e.g.: Sport Recognition).
2. Occupational domains have been left behind.
3. Risk and lesion prevention of WRMSDs can lead to lower fatigue, increasing productivity and efficiency.

Perspective

Disciplines for addressing WRMSDs

Wearable	Predictive Analytics	Cloud	Decision Making
Low Cost Precision	Data Science AI	Infrastructure feasibility	Social and economic value

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Techno-economic feasibility
Is it possible? Is it valuable?

Literature Review

Assessment of WRMSDs

1. WRMSDs of the wrist/hand are highly prevalent among meat cutters [Viikari Juntura, 1983].
2. RULA and OCRA Check List surveys are the standard assessment methodology [McAtamney and Nigel Corlett, 1993, Occhipinti, 1998].
3. Microsoft Kinect 3D cameras or intricate arrangements of IMUs, placed over the worker's body, have been used with good results [Vignais et al., 2013, Buisseret et al., 2018, Chen et al., 2018]
4. Deep Learning black-box models in work environments to detect bad postures [Barkallah et al., 2017, Abobakr et al., 2017, Hu et al., 2018].
5. Practitioners struggle to use IoT technologies to assess risk factors in real industry environments [Lim and D'Souza, 2020].

Perspective

Current Limitations

Predictive Power	Cost	Implementation	Approach
Poor	High	Hard	Biomechanics
Promising	Low	Easy	Data-Driven

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Design Criteria

High Predictive Power, Low Cost, Easy to Implement and Data-Driven.

Section 2

Thesis Hypothesis and Objectives

Objectives

Objective

1. Model the presence of the risk factors during a meat-cutting task as a Time Series Classification problem.
2. Determine if the information obtained from low-cost sensors, placed in the wrists of the worker, and combined with expert supervision, are sufficient to accurately assess the presence of risk factors.
3. Determine if the developed predictive modeling tools for the assessment of WRMSDs can be used to quantify the economic benefits of preventive decision making.
4. Determine if its possible to accurately predict when the worker starts and ends a cut.

Hypothesis

Research Questions

Is it possible to...

1. Gather information from low-cost accelerometers, placed wrists of slaughterhouse workers and use it as input for machine learning algorithms that accurately predict the presence of risk factors in cutting activities.
2. Use the predictions of risk factors as a replacement for human ergonomic supervision and prevention.
3. Assess risk factors with limited human supervision, and only relying on auxiliary predictions.
4. Identify a positive relationship between a reduction in ergonomic risk and productivity.

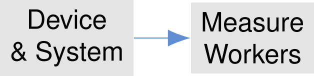
Section 3

Methodology, Prototype & Experiments

At the Beginning

Device
& System

At the Beginning



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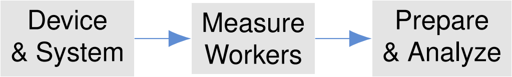

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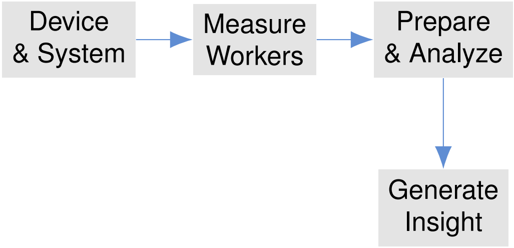

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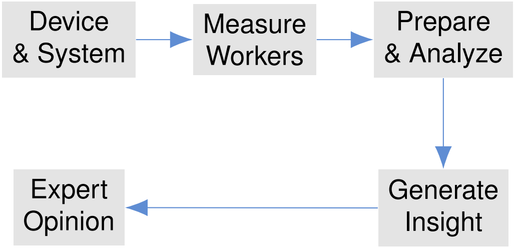

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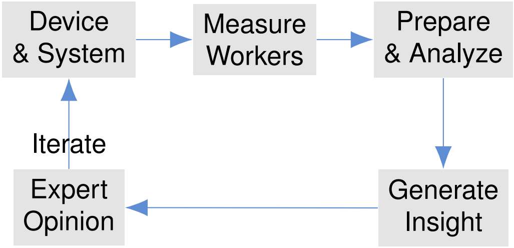

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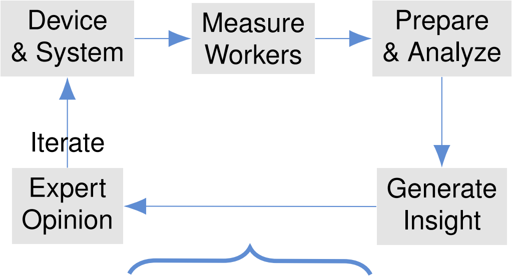


Strategic Guidelines

- Innocuous
- Indicator Evolution
- Task Extrapolation
- Avoid Complexity

Methodology

Resulting Framework

1. We model each risk factor of interest as a supervised learning problem.
2. Hence, for each problem we will need to provide supervision. This is done by performing measurements on workers.
3. Transform sensor data into features that can be used in supervised learning. (e.g. feature matrix in regression problems).
4. Ensemble a supervised learning pipeline: Pre-processing, encoding, standardization, feature engineering, training, validation (via cross validation) and test. On each iteration a set of parameters is used. We choose the best one.
5. Obtain ergonomic insight for decision making.

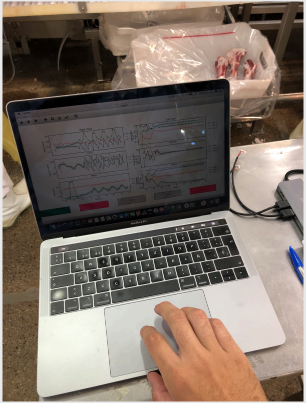
Prototype

Bracelet

Prototype

Bracelet

GUI



Prototype

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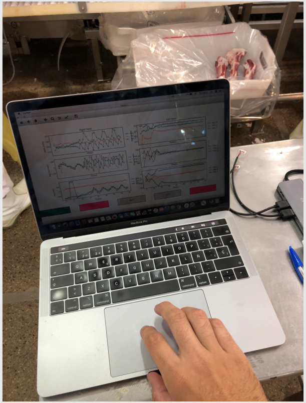

Batch Layer

- Innocuous
- Indicator Evolution
- Task Extrapolatio
- Avoid Comp

Experiments

Sample population

2 instructors and 18 Non-senior workers with varying degrees of experience.

Experiments

Work tasks

Three work tasks.

1. Instructor 1: Complete processing of the meat product
2. Instructor 2: Femur and coxal deboning
3. Non-senior workers: Femur deboning.

Experiments

Assessment of WRMSDs

We propose a workflow for the assessment of WRMSDs based on the application of consecutive machine learning problems, using their predictions as input for a decision making rule.

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