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Energy-Aware Embedded Classifier Design for Real-Time Emotion Analysis

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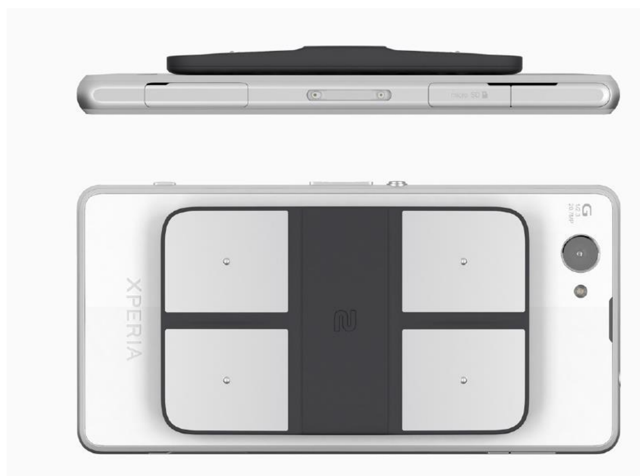
INTRODUCTION

What is Embedded Real-Time Emotion Classification?

- Distinguishing one human emotion from another.
- Making the distinctions at the same time as they occur.
- Mounted on a device which collects physical data.

Why is it Important?

- Continuous monitoring for Alzheimer's disease [1] (Agitation, Disorientation, and Stress).
- Recognition of stress levels in drivers [2].
- Occupational therapy for Autism and ADHD [3], etc.



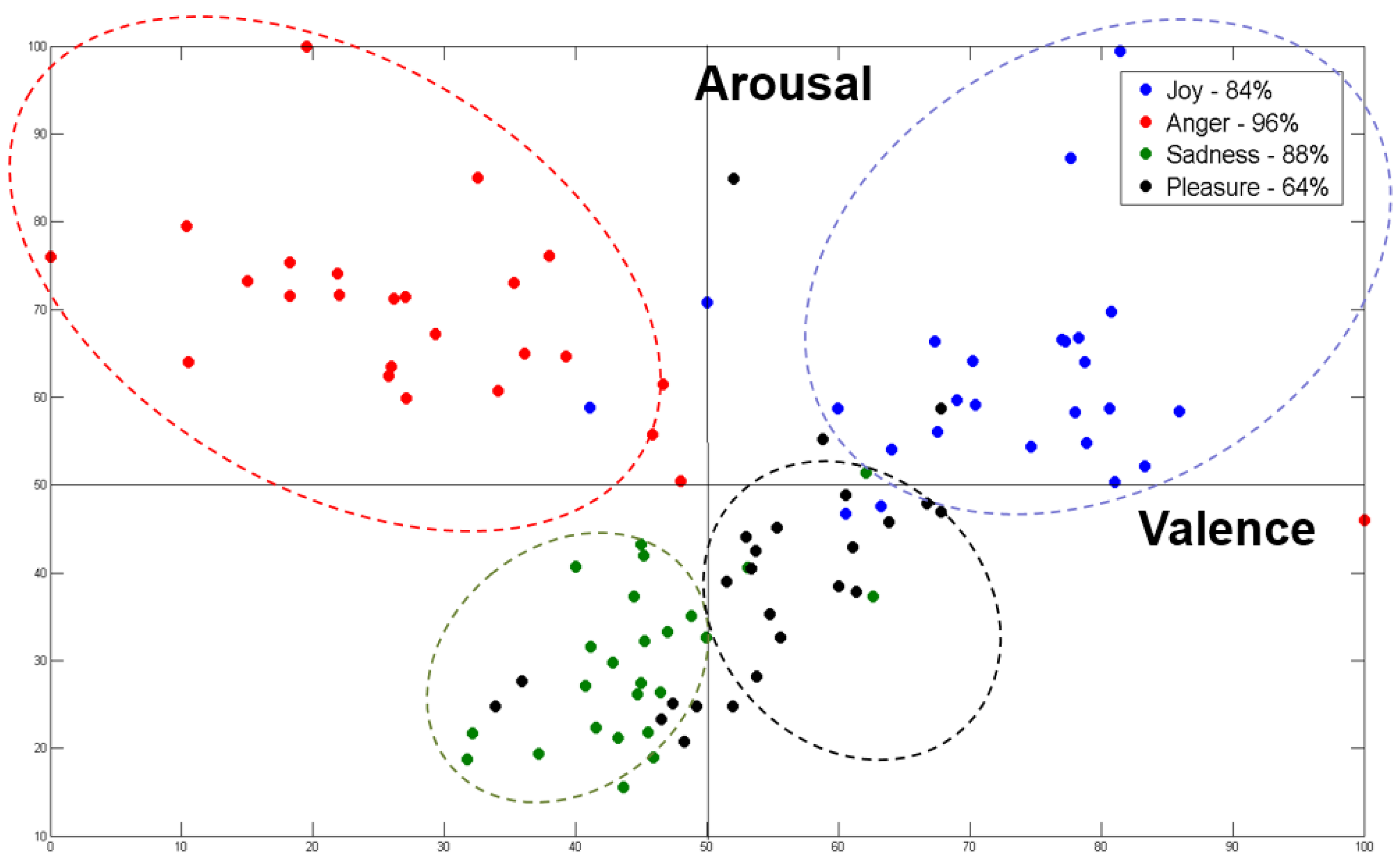
Wearable devices measure multiple physical signals :

- ECG
- Breathing
- Skin conductance

DESIGN METHODOLOGY AND FEATURE SELECTION

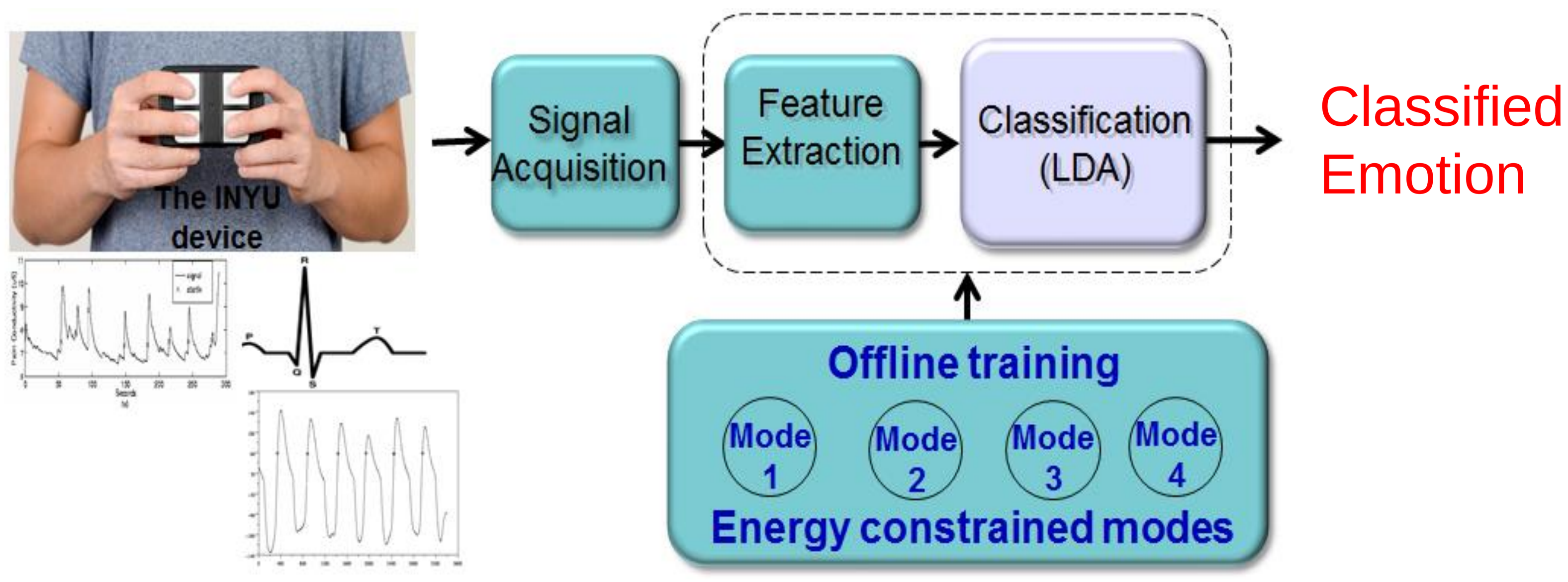
Energy-Aware Operating Modes Design

- What is the Goal? To **maximize** the classification accuracy and to **minimize** the energy consumption in doing so.
- The Smartcardia INYU [4] wearable bio-signal processor is employed to derive all the features (like heartrate, etc.) from the signals.
- An algorithm has been developed to extract features smartly based on a given energy budget.



The two dimensional valence-arousal classification model is used to classify four classes of emotions: *Joy, Anger, Sadness and Pleasure*

Proposed Algorithm Description

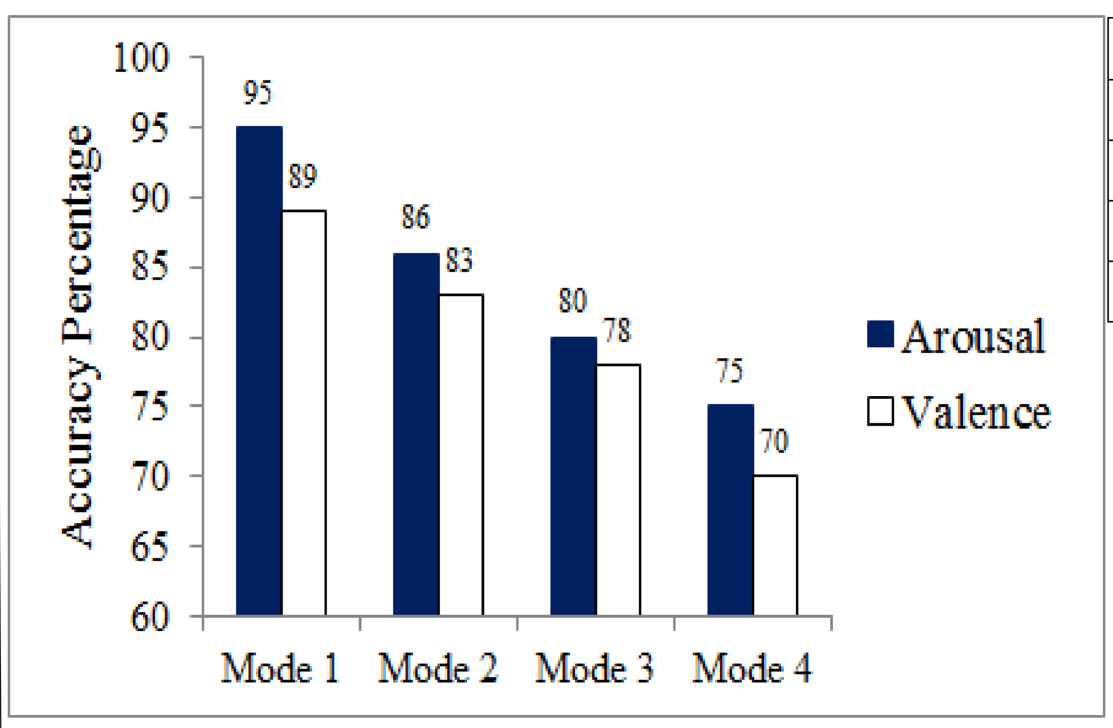


- Mode 1 to 4 are in decreasing order of energy consumption. The number of features selected depends on the operating mode.
- If energy costs of a feature < total energy budget, then find the classification accuracy using it and other selected features.
- Continue adding features until energy budget is exceeded.
- Augment the target feature set with the feature with maximum value for the objective function.

$$\varphi = \alpha A + (1 - \alpha) E$$

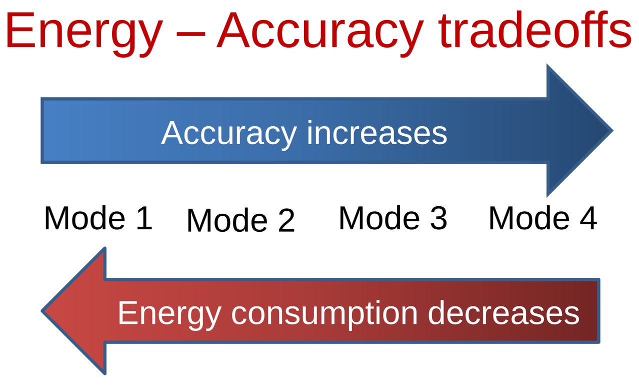
- A = Classification accuracy,
- α = Adaptive weight,
- E = Available energy fraction

EXPERIMENTAL DETAILS AND RESULTS



Mode	Average Current (mA)	Lifetime (h)
1	4.86	146.1
2	1.69	420.1
3	1.09	651.3
4	0.63	1126.9

Energy – Accuracy tradeoffs



The targeted embedded platform is the INYU device. It has a **3.3V, 32 MHz STM32** ultra-low power microcontroller, capable of operating in sleep mode and low power sleep mode. The battery is of **710 mAh** rating at **3.7V**.

CONCLUSIONS

- The accuracy trade-offs range between 95% - 75% and 89% - 70% for arousal and valence classification accuracy respectively.
- The battery lifetimes for the different modes range from 146.1 hours in Mode 1 to 1126.9 hours in Mode 4.

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[1] Samuel Pedro et al., "Sensor-Based Detection of Alzheimer'S Disease-Related Behaviors", The Intl. Conf. on Health Informatics IFMBE Proceedings Volume 42, 2014, pp 276-279.

[2] J. Healey and R. Picard, "Detecting stress during real-world driving tasks using physiological sensors," IEEE Trans. ITS, vol. 6, no. 2, pp. 156 – 166, 2005.

[3] E. Hedman et al., "Measuring autonomic arousal during therapy," in Proceedings of 8th International Design and Emotion Conference, Sept. 2012.

[4] "SMARTCARDIA." [Online]. Available: http://www.smartcardia.com