# An REU Experience in Machine Learning and Computational Cameras

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## MOTIVATION

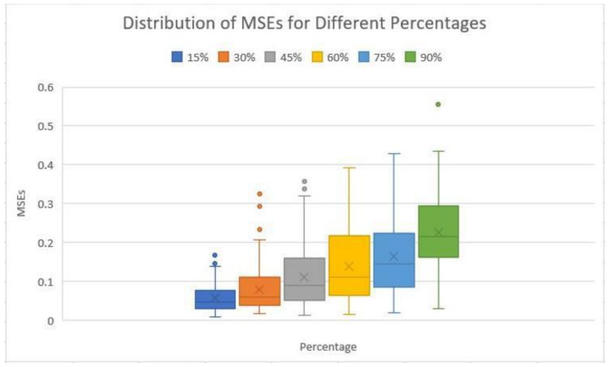
- Efficient integration of undergraduates in STEM research;
- Engineering Solutions for Energy efficiency in Embedded and Mobile platforms;
- Understanding pixel relevance while sensing, to perform computer vision task efficiently.

## PROJECT AIM

- Maintaining Image sensor performance when devoid of a subset of pixels.
- Quantify the energy saved vs computer vision task accuracy.
- Extend the energy saving in video capture by using predictive modeling.
- Training the undergraduate student with basic computer vision techniques.




**Non-Uniform Subsampling Strategies, 1) Original Image, 2) Random Subsampling 3) Checkerboard Subsampling**




**α - controls the amount of Random Pixelation.**

## ADAPTIVE IMAGE SUBSAMPLING ALGORITHM

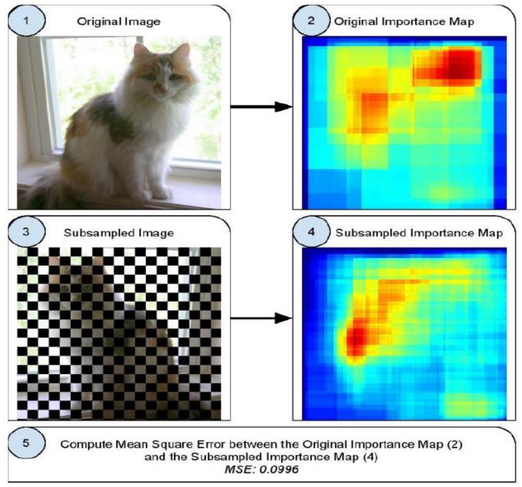
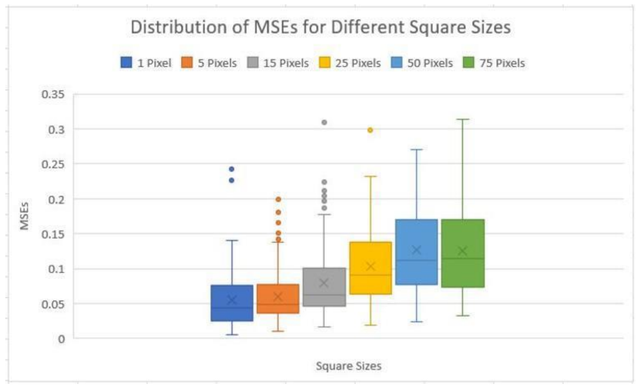


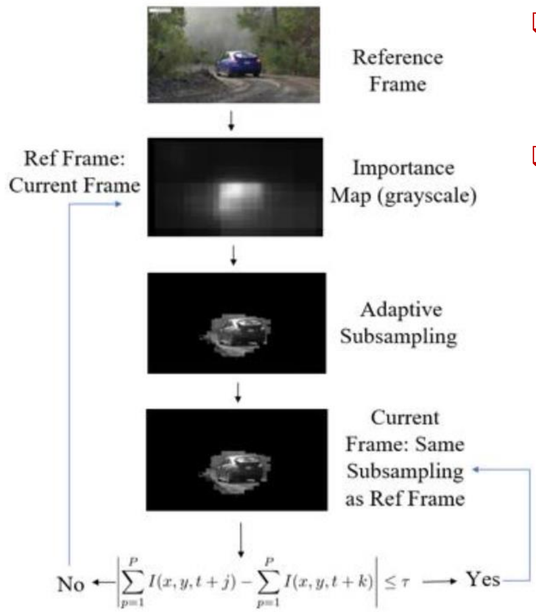

**Diagram demonstrating the process of calculating the Mean Square Error for a Checkerboard subsampling pattern.**

- Quantify the difference using Mean Square Error metric between importance maps from Fully sampled and Subsampled images.
- An ablation study to analyze how the change in the pixelation content affects the objectness.




**Square area- controls checkerboard subsampling.**

## VIDEO BASED ADAPTIVE SUBSAMPLING




- Subsample the next frame in a video given the previous frame's objectness score (called importance map) [1].
- Use techniques in video compression to have key frames which are sampled at full resolution, and other frames are subsampled using optical flow information [2].

**Diagram illustrating the adaptive video subsampling algorithm developed by the REU student and graduate student mentor after the program ended. A reference frame has its objectness/importance map calculated, and then is subsampled. New frames are subsampled with the same strategy until shown intensity-based criteria tells the algorithm to update the reference frame and the importance map.**

## CONCLUSION

- REU program provided a unique opportunity for the undergraduate students to build research skills in sensors and machine learning.
- Student received hands-on programming experience and developed a task specific algorithm for energy efficient computational cameras.

## REFERENCES

[1] Alexe, Bogdan, Thomas Deselaers, and Vittorio Ferrari. "Measuring the objectness of image windows." *IEEE transactions on pattern analysis and machine intelligence* 34.11 (2012): 2189-2202.
[2] Horn, Berthold KP, and Brian G. Schunck. "Determining optical flow." *Artificial intelligence* 17.1-3 (1981): 185-203.

## ACKNOWLEDGEMENTS

**This material is based upon work supported by the NSF under CNS1659871 as well as ASU's SenSIP Center.**

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