

16.2 A Large-Area Image Sensing and Detection System Based on Embedded Thin-Film Classifiers

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Large-area electronics (LAE) enables the formation of a large number of sensors capable of spanning dimensions on the order of square meters. An example is X-ray imagers, which have been scaling both in dimension and number of sensors, today reaching millions of pixels. However, processing of the sensor data requires interfacing thousands of signals to CMOS ICs, because implementation of complex functions in LAE has proven unviable due to the low electrical performance and inherent variability of the active devices available, namely amorphous silicon (a-Si) thin-film transistors (TFTs) on glass. Envisioning applications that perform sensing on even greater scales, this work presents an approach whereby high-quality image detection is performed directly in the LAE domain using TFTs. The high variability and number of process defects affecting both the TFTs and sensors are overcome using a machine-learning algorithm known as Adaptive Boosting (AdaBoost) [1] to form an embedded classifier. Through AdaBoost, we show that high-dimensional sensor data can be reduced to a small number of weak-classifier decisions, which can then be combined in the CMOS domain to generate a strong-classifier decision.

To demonstrate the concept, we develop the system in Fig. 16.2.1. An X-ray imager typically consists of a thin-film scintillator for converting X-rays to photons. We develop an underlying array of photoconductors formed from undoped a-Si, feeding an embedded thin-film classifier, formed from a-Si TFTs. The photoconductors exhibit strong but non-uniform conductivity change in response to illumination, as shown in the measured I-V characteristic. Configured as the leg of a voltage divider, each photoconductor provides an output voltage, shown in response to light and dark conditions. Measurements show substantial variability and even failure of some sensors (Fig. 16.2.1). We overcome these, as well as non-idealities in the TFT classifiers, demonstrating the classification of five shapes with performance at the level of an ideal MATLAB-implemented strong classifier.

Figure 16.2.2 shows the algorithmic block diagram of the AdaBoost classifier. The outputs from N weak classifiers, implemented using TFTs, are provided to a weighted voter (in the CMOS domain) to produce a strong-classifier output. In machine learning, a weak classifier is defined as one that is restricted in its ability to fit arbitrary data distributions, often resulting in substantial classification errors, whereas a strong-classifier is one that can be trained to fit arbitrary distributions. The key benefit of AdaBoost is that the performance required of the weak classifiers is very low, namely only marginally better than 50/50 guessing [1]. This enables simple weak-classifier implementations based on TFTs. In the system, the weak classifiers are nominally implemented as linear classifiers. As shown, each linear classifier, involves dot-product multiplication between an input-signal vector \vec{x} , whose elements correspond to the M sensor outputs, and a classification vector \vec{c}_i , whose elements correspond to weighting biases provided from one-time training. The dot-product result is then compared to a threshold for binary classification. Recent work has shown that weak-classifier errors due to hardware imperfections can be overcome without the need to explicitly characterize or model the imperfections. This is because AdaBoost performs weak-classifier training iteratively, enabling the errors from previous weak classifier iterations to be fed back and compensated for during training of subsequent iterations [2]. In our system demonstration, this one-time training is performed offline; however, the training algorithm can be implemented in an embedded CMOS IC (as in [2]), with the classification vectors $\vec{c}_1 \dots \vec{c}_N$ from N iterations of training provided through a low-speed serial interface (such as [3]). In our implementation, number of sensor outputs M is 36, and number of weak classifiers N is 2 to 5, demonstrating that substantial reduction of the raw sensor signals is achieved.

Figure 16.2.3 shows the implementation of the TFT-based classifier, which processes the sensor outputs $V_{S,1-36}$ using the weighting biases $V_{B,1-N,1-36}$ (these are realized via programmable TFTs, as described below). To approximate a linear classifier, the element-wise multiplication required within the dot product is implemented as the output current from a branch of two series-connected TFTs. Two such branches are configured as a sub-unit to implement pseudo-differential outputs, enabling multiplication by positive and negative weighting biases, as required from training. The summation required within the dot

product is implemented by combining the branch currents within a weak classifier through a load resistor R_{WC} . The resulting differential dot-product outputs $V_{O,1-N}$ can be provided to a CMOS IC for threshold comparison and weighted voting, which is found to be somewhat more sensitive to computational errors [2], and thus best performed in CMOS. Fig. 16.2.3 shows the multiplication transfer function achieved by a two-TFT branch, along with measurement bars illustrating variations across 15 instances. Both substantial variation and deviation from the ideal multiplication transfer function is observed. Nevertheless, as shown below, the system is able to achieve strong-classifier performance.

The programmable weighting biases $V_{B,1-36,1-N}$ can be implemented by a range of thin-film memory architectures/devices (e.g. [4]). Figure 16.2.4 shows the approach used in the system. We make use of deliberate threshold voltage shifting in a conventional a-Si TFT due to charge trapping in the silicon nitride dielectric, which can be induced (removed) by high positive (negative) gate electric field. Programming a threshold voltage shift in the range of 0-30V (as required from weak-classifier training) is accomplished by applying a gate-source programming/erasing voltage of 80V for 1ms-100s. The programmable TFT is chosen to be the lower device within the multiplier branches to ease application of the programming voltage. Reliable threshold voltage shifting is achieved with respect to programming time, with a measured standard deviation $<1.0V$. Experiments explicitly applying random variation in $V_{B,1-36,1-N}$ with σ of 1.5V suggest that this level of variation is robustly tolerated. While the approach used incurs long programming times, optimizations of charge traps in the gate nitride have shown that these times can be substantially reduced [4].

To demonstrate system functionality and performance, we perform image classification of five shapes (cross, tee, el, triangle, ring) by training the system in each case as a one-versus-all classifier. The a-Si 6x6 photoconductor sensor array and TFT weak classifiers are both fabricated on glass substrates at process temperatures $<180C$ (separated samples are fabricated to facilitate testing). The dataset consists of 150 instances corresponding to various shading and lighting conditions (dark, ambient, bright) for the shapes, which are displayed onto the thin-film photoconductor array using a micro-projector. Conventional five-fold validation is performed to divide the dataset into training and testing subsets. In addition to providing the sensor outputs to the TFT weak classifiers for detection by the system, the raw sensor outputs are acquired for evaluation. In particular, the acquired data is used for training and classification by a MATLAB-implemented support vector machine (SVM) with radial-basis-function kernel [5], which is a widely used strong machine-learning classifier. The measured results, corresponding to true-positive (tp) and true-negative (tn) rates following each iteration of weak-classifier training, are shown in Fig. 16.2.5. Boosting of the TFT classifier is demonstrated by the performance improvement achieved with each iteration, eventually converging to high tp/tn ($>85\%/>95\%$). As seen, in all cases, the TFT-based classification system achieves performance close to that of an ideal SVM, with just 2-5 iterations, thus substantially reducing the signals required for image detection.

Fig. 16.2.6 shows the experimental setup and summarizes the classifier system performance. The micro-projector and breakout board used to facilitate testing of the thin-film sensor array and TFT classifiers are shown. Micrographs of fabricated a-Si photoconductors and TFT weak classifiers are in Fig. 16.2.7.

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References:

- [1] R. Shapire and Y. Freund, *Boosting: Foundations and Algorithms*, The MIT Press, 2012.
- [2] Z. Wang, R. Shapire, N. Verma, "Error-Adaptive Classifier Boosting (EACB): Exploiting Data-Driven Training for Highly Fault-Tolerant Hardware," *IEEE Int'l Conf. on Acoustics, Speech and Signal Processing*, pp. 3884-3888, May 2014.
- [3] T. Moy, et al., "Thin-Film Circuits for Scalable Interfacing Between Large-Area Electronics & CMOS ICs," *Device Research Conf.*, pp. 271, June 2014.
- [4] Y. Huang, S. Wagner, J.C. Sturm, "Nonvolatile a-Si Thin-Film-Transistor Memory Structure for Drain-Voltage Independent Saturation Current," *IEEE Trans. Electron Devices*, vol. 58, no. 9, pp. 2924-2927, Sept. 2011.
- [5] N. Cristianini and J. Shawe-Taylor, *An Introduction to Support Vector Machines and Other Kernel Based Learning Methods*, Cambridge University Press, 2000.

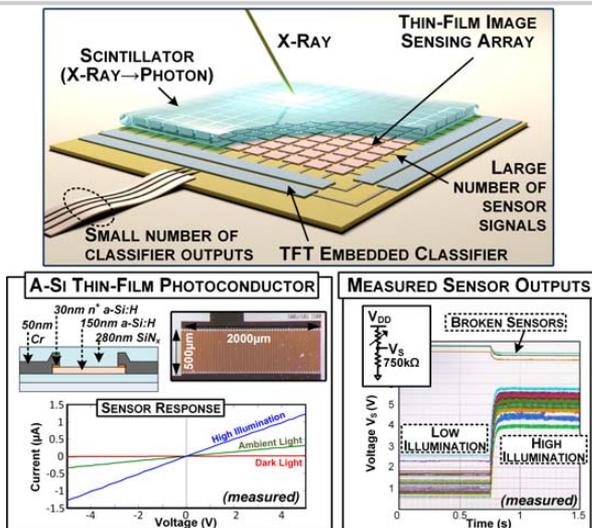


Figure 16.2.1: System architecture, constructed out of non-ideal thin-film a-Si photoconductors and transistors.

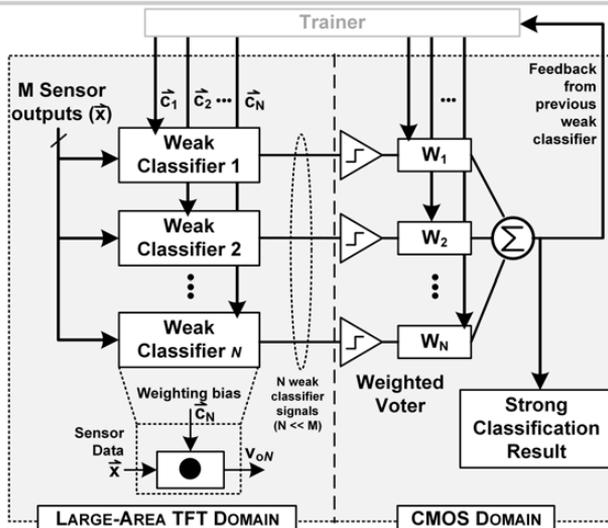


Figure 16.2.2: Architecture of the classification system consisting of TFT linear weak classifiers trained using the AdaBoost algorithm.

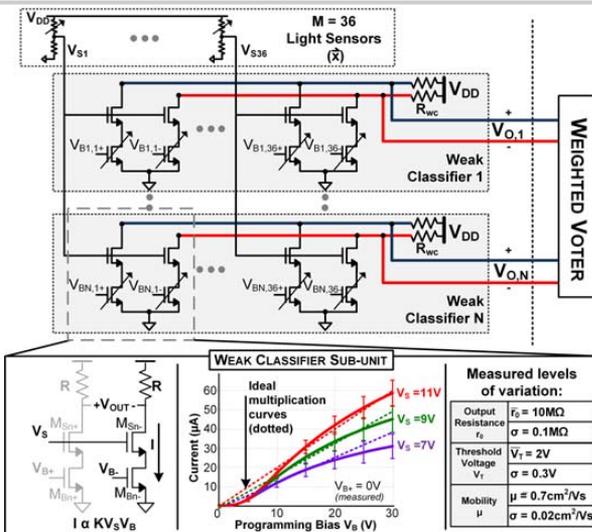


Figure 16.2.3: Implementation of TFT-based linear weak classifiers. Weighting biases ($V_{B1-N,1-36}$) are applied via programmable TFTs.

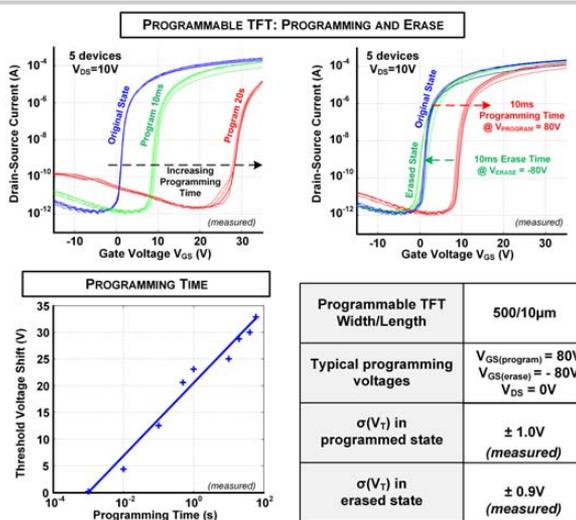


Figure 16.2.4: Programmability required for weighting biases achieved by deliberate threshold-voltage shifting of a-Si TFTs at high gate fields.

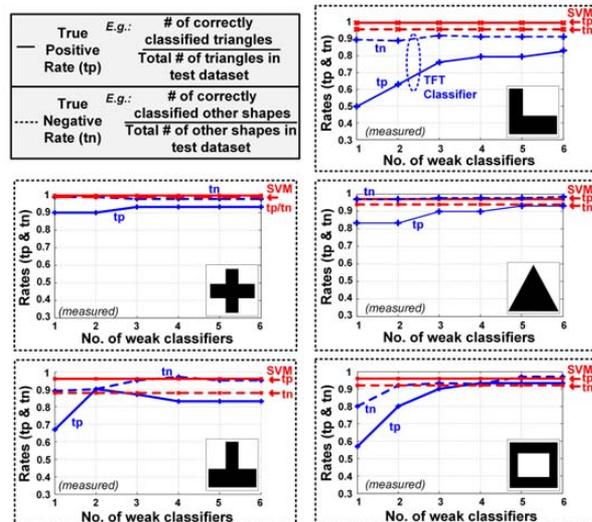


Figure 16.2.5: Performance of fabricated TFT system demonstrates classification performance near that of an ideal SVM.

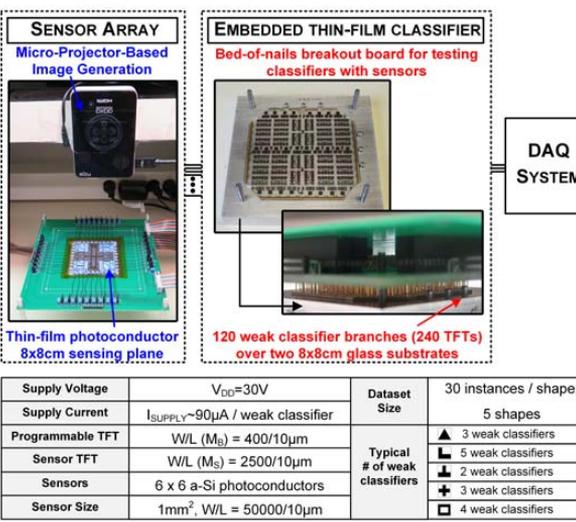


Figure 16.2.6: System prototype, test setup, and performance summary of the thin-film image sensing and classification system.