Identification of process non-uniformity sources in microbolometer Infrared sensor arrays

Raghvendra Sahai Saxena*, Rajinder Kumar Bhan, Chanda Ram Jalwania, Anita Aggarwal, Kumkum Khurana and Surender Kumar Lomash
Solid State Physics Laboratory, Lucknow Road, Timarpur, Delhi-110 054 (India)

ABSTRACT

We present here a statistical method for identification of the sources of process-induced non-uniformity in 16x16 arrays of microbolometer IR sensors using principal components analysis. Due to the random variations in various processing steps, the parameters are varied and distributed randomly over the whole area of the sensor array. To identify and control the process steps having major contribution to this non-uniformity, we have performed the correlation study and principal component analysis on a number of these arrays. As a result of this analysis, we found TiN layer deposition to be the leading source of non-uniformity in our case. The support-leg etching and the Ti film thickness variation are the other minor contributors of this non-uniformity. This work is beneficial for improving any fabrication process resulting in the yield enhancement.

Keywords: MEMS, Microbolometer, Principal Component Analysis, IR detector, Process non-uniformity

1. INTRODUCTION

MEMS based microbolometers are the attractive candidate for infrared sensing because of manufacturing ease, low cost, no cooling requirement and compactness [1-4]. Maintaining the pixel-to-pixel response uniformity in IR imaging arrays of these sensors is a critical issue. This is very important for faithful reproduction of the defect free image of the scene. The sources of non-uniformity (NU) are the statistical variations in various fabrication steps and they limit the fabrication of large 2D arrays. Therefore, it is important to analyze the processing variations to have a control on process induced NU.

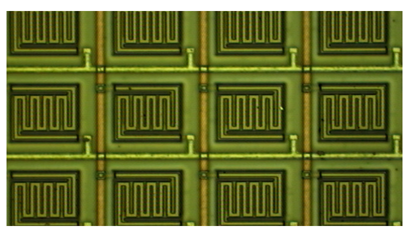
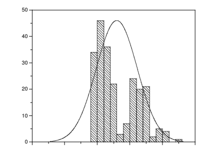
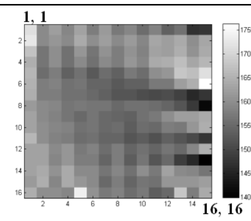
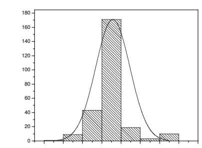
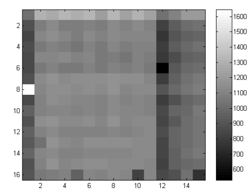
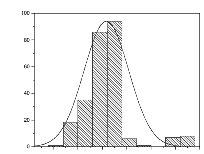
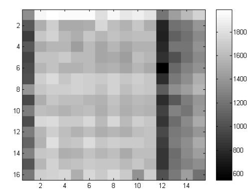
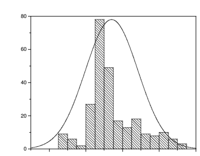
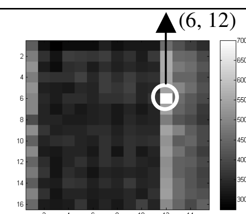
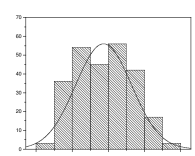
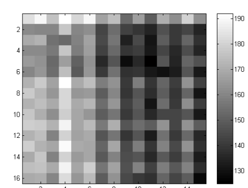
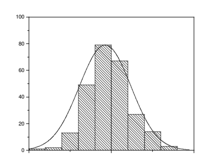
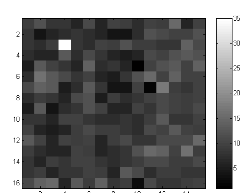


Fig. 1. Photograph of a part of a typical 16x16 microbolometer array

We present here the use of correlation coefficients and principal component analysis (PCA) [5, 6] to analyze the physical sources limiting the fabrication uniformity of 16x16 arrays of Ti-microbolometers being developed at our laboratory [7-9]. A photograph of the part of our typical array is shown in figure 1. The measurement results on some of arrays have shown NU more than 10% [8, 9]. We analyzed the spatial and statistical variations of six different performance parameters over the arrays to quantify their correlation and then performed the PCA for identification of major source of this NU. We obtained various physical sources limiting the uniformity of the arrays with their relative contribution in overall NU.

*rs_saxena@yahoo.com; 580@ssplnet.org; Phone: 011-23903765

Table. 1. Representative parameters and their statistical and spatial distribution for Principal Component Analysis

Parameters	Description	Statistical Variation	Spatial Variation
1. Room temperature Resistance (R_0).	• Obtained directly by simple IV measurements. • It contains the information of Ti metal layer deposition process and the electrical contacts.	 σ = 2.1% of mean	
2. TCR to Thermal Conductance Ratio (α/G).	• Extracted by the slope of 1/R vs I^2 plot. It represents the thermal response. • It contains the information of the quality of Ti film and the support leg structure.	 σ = 10.6% of mean	
3. Resistance Change for ΔI = 500μA (ΔR_{500}).	• Evaluated directly from DC IV characteristics. • It contains the information of thermal isolation of the elements from environment.	 σ = 17.5% of mean	
4. Current Change for ΔR=1Ω (I_M).	• The crossover with 1Ω line in ΔR-I Plot obtained by the IV measurements. • It is indicative of thermal response time and contains the information of thermal mass.	 σ = 17.6% of mean	
5. Response to IR radiation (Signal).	• Electrical signal generated by the chopped blackbody radiation. • It contains the information of TCR and IR absorbance.	 σ = 9.5% of mean	
6. Noise (v_n).	• This is the rms variation in signal, during radiometric measurements. • Contains the overall health of the element.	 σ = 16.1% of mean	

2. THE DEVICE STRUCTURE

The IR sensing elements are made hanging on the silicon substrate in 16x16 array fashion. These are made of 700 angstroms thick Ti film in a serpentine shape, sandwiched between 0.35 µm bottom and 0.60 µm top membranes of Si_3N_4. An air gap of 2.0 µm has been kept between the bottom of membrane stack and the substrate. Two Ti hinges support this membrane stack and provide electrical and thermal connectivity. Additionally a TiN layer is deposited on the top to increase the IR absorbance by utilizing its property of impedance matching with the free space. Various arrays of 16x16 configuration having different pixel sizes and hinge length/width have been fabricated. Here the results are reported for 50x50 μm^2 pixel dimensions and 75x2 μm^2 support leg dimensions bolometer arrays. The fabrication details are discussed in ref. [7].

3. EXPERIMENTAL DETAILS

We have selected some highly non-uniform, but defect free devices, i.e., having no open or short circuited element. We performed a detailed radiometric measurement and IVT characterization and extracted various performance parameters [8, 9]. The six parameters, as listed in table 1, have been selected for analyzing the NU in these devices. We analyzed the variations of these parameters on a number of arrays. Table 1 displays the spatial and statistical variations for a typical array. We mapped the data from the domain of correlated (measured) parameters to the domain of uncorrelated new parameters. These new parameters are constructed by the combination of measured parameters, called principal components (PCs). This technique is known as PCA. In this technique, the co-variance matrix of the data is computed [5] and its 'unit eigen-vectors' give corresponding PCs. A left matrix-multiplication of PC matrix and the original data matrix transform the data into new domain defined by the PCs. Following PCA technique, we obtained six PCs, namely P1 to P6 in our devices.

3.1 Correlation Study

The spatial distributions may be seen in the figures shown in table 1 qualitatively, e.g., a good correlation among parameters 2, 3, 4 and 5 is visibly apparent for element (6, 12). A gray-scale intensity map of the absolute correlation coefficients of the six parameters is shown in figure 2. Here, the bright intensity signifies the strong correlations. We see that parameters 2, 3 and 4 have a good correlation with each other and the parameter 1 is weakly correlated with all other parameters, accept parameter 5. These correlations may be analyzed for the overall device behavior, e.g., the parameter 2 signifies the amount of heat retained by the element that results in high resistance change for a given current. The same may be concluded from the correlation between parameter 2 and 4. However, this information is not sufficient to uncover the main variance contributor. Therefore, we used PCA to analyze the physics underlying the variance.

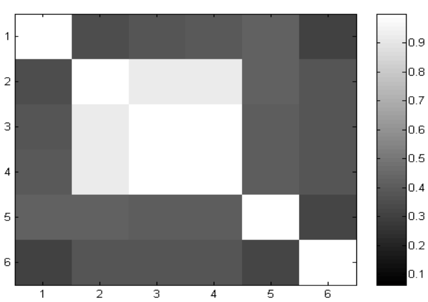


Fig. 2. Correlations among parameters

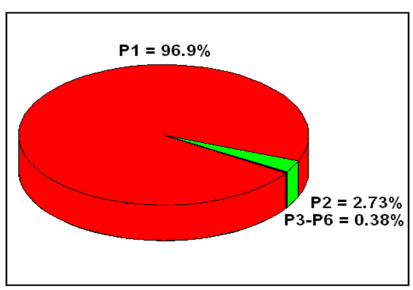


Fig. 3. Relative variance of PCs

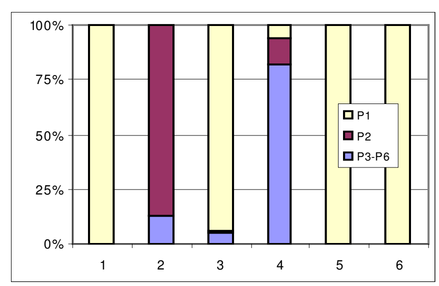


Fig. 4. The impact PCs on parameters

3.2 Principal Component Analysis

The six PCs obtained for our device, namely P1 to P6 are shown with their relative variance contributions in figure 3. The P1 and the P2 have significant contributions of 96.9% and 2.73% of the total variance, respectively, whereas the other principal components, i.e., P3 to P6 have a very little contribution of 0.38%, collectively. The elements of principal component unit vectors are the scaling factors of the initial variables, when scaled and added give the transformed data in new domain. To identify the leading PCs, we found the relative impact of these on our chosen parameters, as shown in figure 4. Here, we see that the P1 has a strong contribution in most of the parameters, except parameters 2 and 4. Out of these, parameters 1, 5 and 6 are completely dominated by the P1. The P2 is contributing to 2, 3 and 4 significantly. The other components have combined impact on only parameters 2 and 4.

4. RESULTS AND DISCUSSION

Now, from figure 4 it may be inferred that P1 is responsible mainly for the electrical properties of the detectors, whereas P2 governs the thermal properties. It is also clear that the electrical property variations are more significant than thermal. We repeated our analysis on some more devices, having considerably high NU and found the similar behavior of the PCs. We also found that the process variations affecting the parameter 2, i.e., TCR to G_{Th} ratio are not responsible for the signal variations, though it is linked with signal. It leads to the conclusion that the process step strongly affecting the signal but not contributing to its thermal behavior is the major source of non-uniformity. This is possibly no other than the IR absorption layer of TiN. The other thermal property variations, governed by P2, occur due to the faults in support-leg structures and Ti film quality.

5. CONCLUSIONS

We have presented a statistical analysis technique based on PCA on 16x16 IR detector arrays of Ti-microbolometers to find the major source of non-uniformity in the fabrication of these arrays. We have shown using the experimental data that the TiN layer deposition is a leading source of non-uniformity in our case. The support-leg etching and Ti film thickness variation are the other less important non-uniformity contributors in our arrays.

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