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# PACKAGING ELECTRONICS ON TEXTILES: IDENTIFYING FIBER JUNCTIONS FOR AUTOMATED PLACEMENT

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## ABSTRACT

*Electronic textile (E-textile) research requires an understanding of the mechanical properties of fabric substrates used to build and support electronics. Because fibers are often non-uniform and fabrics are easily deformed, locating fiber junctions on the irregular surface is challenging, yet is essential for packaging electronics on textiles at the resolution of single fibers that deliver power and signals. In this paper, we demonstrate the need to identify fiber junctions in a task where microelectromechanical structures (MEMS) are integrated on fabrics. We discuss the benefits of fiber-aligned placement compared with random placement. Thereafter we compare three image processing algorithms to extract fiber junction locations from sample fabric images. The Hough line transform algorithm implemented in MATLAB derives line segments from the image to model the fibers, identifying crossings by the intersections of the line segments. The binary image analysis algorithm implemented in MATLAB searches the image for unique patterns of 1s and 0s that represent the fiber intersection. The pattern matching algorithm implemented in Vision Assistant- LabVIEW, uses a pyramid value correlation function to match a reference template to the remainder of the fabric image to identify the crossings. Of the three algorithms, the binary image analysis method had the highest accuracy, while the pattern matching algorithm was fastest.*

Keywords: MEMS, Packaging Electronics on Textile, Hough Line Transform, Pyramidal Value Correlation, Image Processing

## 1. INTRODUCTION

E-Textiles can be viewed as a variation on thin film-based flexible electronics for making large area devices. Fabrics have become a favorable and desirable substrate for integration of electronic devices owing to their porous, flexible, breathable, mechanically strong, and multimaterial nature [1]. In addition, the structural properties of the fabric such as fiber density, weave pattern, fiber intersections, yarn number and crimp [2] [3] are essential to analyze as the fabrics are more irregular than thin films commonly used to build and support electronics. Automatic woven textile structure recognition techniques have been prevalent in the textile industry, and image processing techniques [4] such as integral projection method [5], Fourier transform techniques [6], [7], and fuzzy c-means clustering [8] have been extensively used to analyze the structural properties. Based on how fiber junctions are composed, a junction can be a potential ohmic contact, capacitor, insulating crossover, or even a semiconductor junction, thus realizing logical circuits such as multiplexers on fabric. For example, wire electrochemical transistors are realized by placing two PEDOT/PSS coated fibers in a cross geometry and creating an ionic contact at the junction of fibers [9]. In another example, a fiber based fabric array memory device was implemented where the number of available bits was a direct function of the number of interconnections in the fabric [10].

From a broader application viewpoint, for electronics being packaged on a fabric it is essential to know the positions of conductive threads and other types of fibers such as insulators, optical fibers, and actuators such as shape memory wires and heater wires. Therefore, it is essential to identify not just fiber intersections but fiber types.

Conventional circuit fabrication can tolerate misalignment because surface tension pulls small parts into alignment during soldering. Likewise, for fabric packaging we seek statistical methods to overcome the discrepancies of a fiber network over stretching, shrinking, and distortion.

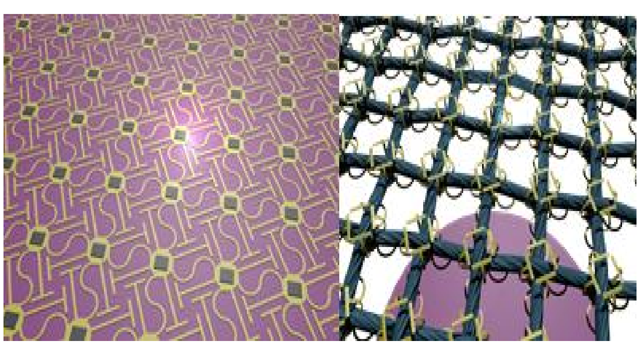
In this paper, we demonstrate the integration of MEMS gripper devices with fabric having random alignment. Figure 1(a) is an idealized vision showing how the grippers curl up from a wafer to attach electronic devices to the underside of a fabric. The actual integration of MEMS structures with fabric is highly irregular due to the non-uniform loom woven fabric, for example Figure 1(b), and random device alignment without foreknowledge of the intersection locations.

Thanks to increased speeds, it is becoming practical to use direct-write lithography systems to write a single custom MEMS layout. The layout could potentially be customized to a fabric swatch. But first we need to extract the fabric structure and use it to lay out the design. Three image processing algorithms are discussed for identifying fiber crossings:

1. Hough Line Transform algorithm identifies fiber crossings as intersections of line segments which are used to model the fiber threads.
2. Binary image analysis identifies crossings as unique patterns of 1s and 0s.
3. Correlation value pyramid pattern matching implemented in Vision Assistant- LabVIEW, compares a reference template to the image to extract fiber intersections.

Test Fabric swatches with varying fiber density, irregular fiber spacing, curved fiber paths etc., are created to replicate the discrepancies of an actual fabric. The three algorithms are implemented on these test swatches to extract fiber intersection information, and the results are illustrated. With the knowledge of the intersections in a fabric, we then demonstrate how to employ T-cells, a programmable CAD object, to customize MEMS gripper designs toward the integration of MEMs devices as idealized in Figure 1.

(a)



(b)

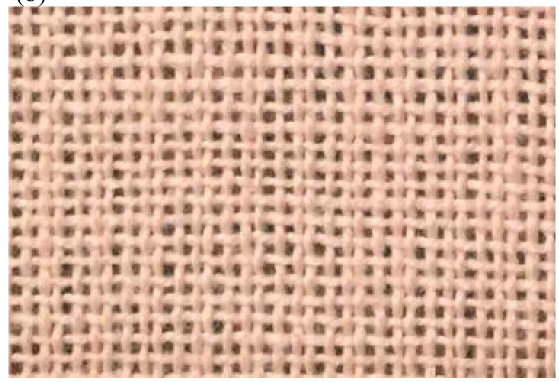


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**FIGURE 1: a.** ABOVE LEFT & RIGHT: ELECTRONIC LAYOUT PAIRED WITH HIGHLY REGULAR FABRIC FOR PACKAGING ELECTRONICS; **b.** ACTUAL LOOM-WOVEN FABRIC IS NOT PERFECTLY UNIFORM. NON-UNIFORM FIBER DIAMETERS, UNEVEN SPACING, AND SLIGHTLY CURVED FIBER PATHS ARE COMMON IN REAL FABRICS.

## 2. MATERIALS AND METHODS

### 2.1 Mechanical gripping as a method to connect electronics to fibers

In this work, we use "pop up" microgrippers to make mechanical and electrical contact between MEMS and fibers. Bilayer cantilevers arranged in a circular fashion as shown in the figure 2 are designed to clasp at the intersections in the fabric.

Strain mismatched bilayer grippers are fabricated as follows: 130nm thick Chrome layer is deposited on an oxidized wafer with 400 nm thick oxide. Photolithographic patterning is done to imprint the gripper design on the wafer, followed by wet chrome etching and plasma assisted oxide etch. The fabric is randomly aligned and placed over the die. The gripper structures are released through isotopic Si etching in a $XeF_2$ (Xactix, Inc.) chamber. The strain mismatched bilayers curl when released and clasp on to the fabric mesh. The process is detailed further in [11] and the fabrication process is illustrated in figure 3.

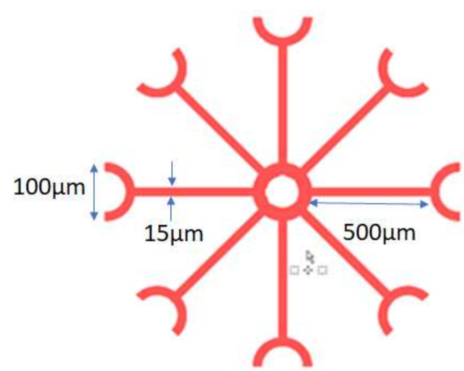


**FIGURE 2:** GRIPPER LAYOUT

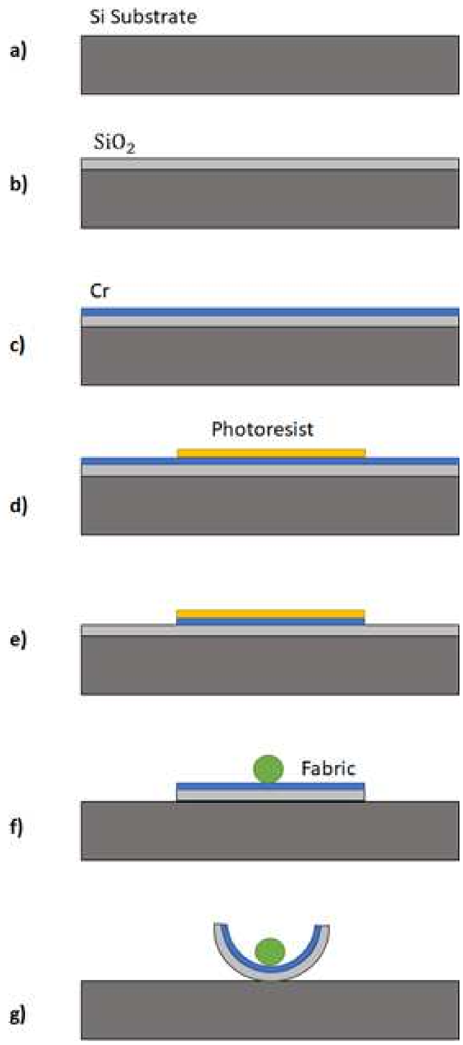


**Figure 3:** FABRICATION PROCESS A) SI WAFER B) SIO2 DEPOSITION C) CR DEPOSITION D) PHOTOLITHOGRAPHIC PATTERNING E) CR ETCHING F) SIO2 LAYER ETCHING USING METAL LAYER AS THE MASK G) ALIGNMENT OF PATTERNED STRUCTURES WITH FIBER INTERSECTIONS G) XEF2 ETCHING TO RELEASE THE STRUCTURES TO GET MECHANICALLY ATTACHED TO THE FIBER CROSS SECTION

## 2.2 Creating test swatches for fabric feature identification

Test swatches were made to replicate the discrepancies of an actual fabric such as uneven spacing of the fibers, non-uniform fiber diameters, splits within each fiber, and slightly curved fiber paths (Figure 3). White reflective threads are stitched on the black cloth which is used to provide a contrast background. Color threads are included to have unique color intersections for identification. The color threads are used to model functional fibers such as conductive, insulated, or optical fibers etc., that need to be uniquely identified among ordinary threads, for a macroscale application. One example is packaging temperature-sensing electronics on fabrics having heater wires.

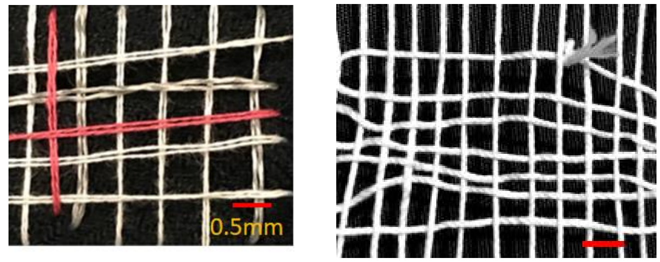


**FIGURE 4:** TEST SAMPLES MODELLING A REAL FABRIC. LEFT: FABRIC WITH FIBRES OF DIFFERENT COMPOSITIONS. RIGHT: FABRIC WITH CURVED FIBRE PATHS (SCALE BARS 0.5 mm)

## 2.3 Three methods for identifying intersections

### Hough Line Transform Algorithm

The fiber crossings in a fabric can be detected through a feature extraction algorithm extensively used in image analysis called the Hough line transform. The fibers in a mesh can be approximated to be line segments, thus detecting fiber crossings as intersections of these line segments. In this algorithm, a 2D matrix is used to represent a detected line defined in polar coordinates as follows:

$$y = (cos\theta/sin\theta)x + (r/sin\theta) \quad (1)$$
$$r = xcos\theta + ysin\theta \quad (2)$$

The algorithm determines the possibility of a line feature in the image that passes through each pixel at (x,y) and computes the (r,ϴ) parameters of the line and stores in another 2D matrix that has the information of the unique line segments in the image. The algorithm is implemented in MATLAB's Image Processing Toolbox (MathWorks, Inc.) , with binary image as the input, the 'hough' function returns the (r,ϴ) parameters and H, the standard Hough transform matrix which is used as input for the 'houghpeaks' function. The most likely feature to be called a line is determined with the help of the 'houghpeaks' function which uses threshold to compute the peaks. In our case the threshold is 30% of maximum 'H' while detecting 100 lines. The 'houghlines' function returns the end points of the line segments for various (r,ϴ) parameters, with binary image, (r,ϴ), Hough transform matrix and peaks as the inputs. Appropriate conditions are applied so that the ϴ values either lie between -5 and 5 degrees or between 85 and 95 degrees. The accuracy of line detection largely depends on efficient edge detection and accurate input parameters.

### Binary Image Analysis

In this method we developed, the original image is converted to binary after being obtained under a highly contrasting background. In our case, the fibers and the background account for the two different values of the binary image. Crossings of the fibers are determined as a series of white pixels crossing a nearly perpendicular series of white pixels. This algorithm detects a mass of points at the crossing of the fibers, computing the centroid of which gives the single pixel information of the crossing.

This algorithm is implemented in MATLAB, wherein 'rgb2gray' function is used to convert the colored image to grayscale and 'imbinarize' function is used to obtain the binary matrix of the image. The following image is an example of ideal binary matrix for our algorithm, wherein vertical series of 'ones' representing the length of the fiber cross horizontal series of 'ones' representing another fiber. Here, the crossing pixel is identified by the pixels it is surrounded by. In a real scenario, the fiber thickness will correspond to more than one pixel. This results in a collection of points being identified at the intersection, whose centroid can be used as the location of the crossing. This algorithm sustains errors such as uneven spacing of the fibers. Curved fiber paths are sustained to a large extent, but crossings at certain range of acute angles such as between 30 to 60 degrees can be misleading.

| | | | | |
|---|---|---|---|---|
| 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 |
| 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 |

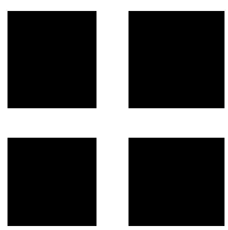

**FIGURE 5:** (LEFT) BINARY MATRIX EQUIVALENT OF AN IDEAL BINARY IMAGE OF THE FIBER CROSSINGS (RIGHT)

### Correlation Value Pyramid-Pattern matching

The fiber cross sections can also be identified by feature matching to a reference template of the intersection in the image. A prevalent pattern of the fiber crossing is chosen as the reference template. The pattern matching algorithm is a twostep process consisting of image acquisition and matching implemented in Vision Assistant- LabVIEW. The algorithm acquires either the gray value information complementing the fine textures and dense edges in the image or the edge gradient information from the filtered pixels at the edges on the basis of illumination and resolution of the image. Subsequently pattern matching is done through normalized cross correlation. This step is time consuming as it involves serial multiplication; to increase the computational speed, the algorithm employs a pyramidal matching technique wherein using the gaussian pyramidal function, the image as well as the reference template are sampled to a quarter of their original sizes at each pyramidal level. This step allows faster computation but works at lower resolutions.
The matching pattern of the fiber cross-section is evaluated based on the matching score which is 100 for the reference template itself. Patterns with matching score greater than 80 are identified as fiber crossings.

## 2.4 Customizing the Gripper Design in L-Edit: T-Cells

Based on the fiber intersections data from the algorithms, we customize the gripper design by defining the design parameters such as gripper length, gripper to gripper distance etc. In L-Edit software (Tanner, Inc.) this task can be automated using programmable T-Cells which allow us to change parameters by defining 1D "ports" for H-Stretch, V-Stretch etc.

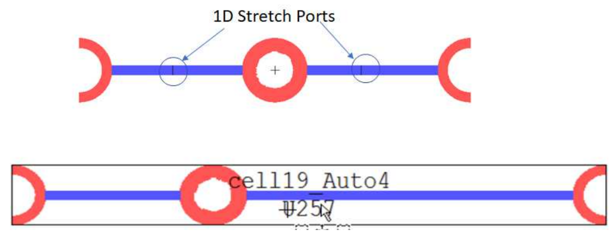


**FIGURE 6:** GENERATING INSTANCES OF T-CELLS WITH DIFFERENT PARAMETER VALUES FOR STRETCH PORTS. 200 MICRON GRIPPER LENGTH STRETCHED TO 486 MICRONS

## 3. RESULTS AND DISCUSSION

*3.1 Results of clasping success or failure vs distance from randomly aligned fibers*

Fabric mesh with diameter 50 to 100-micron range and having mesh openings in the 500 microns to 1 mm diameter range was randomly aligned and placed on the MEMS bilayer gripper structures on the Si wafer. The structures were released from the Si substrate and were transferred to the fiber substrate through curling and mechanical tangling due to strain mismatch in the bilayer of Chrome-oxide grippers. The grippers at a relative distance (distance from the gripper center to the mesh fiber in units of mesh width) of less than 0.4 from the fiber successfully got hold of the fabric while at relative distances greater than 0.4, most of the gripper arms missed the fabric. Figure 6 shows the binary clasping versus the relative distance from the mesh fiber. And Figure 7. pictorially compares a successful clasp versus an unsuccessful one.

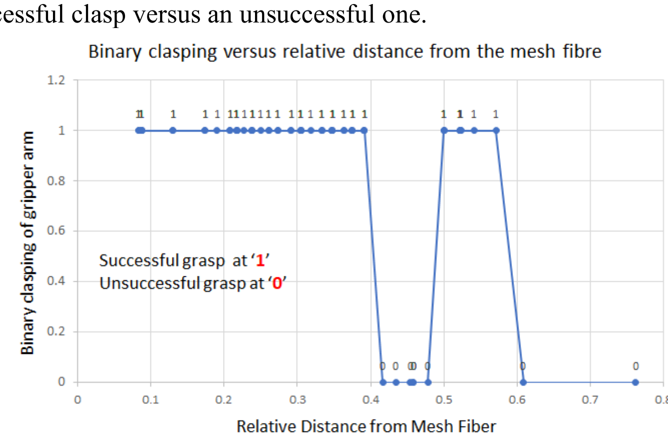


**FIGURE 7:** BINARY CLASPING VERSUS RELATIVE DISTANCE FROM THE MESH FIBRE

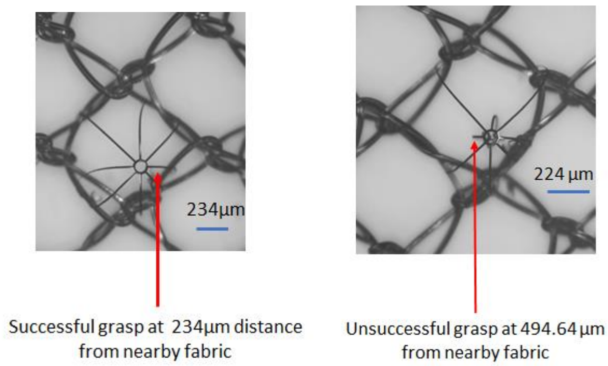


**FIGURE 8:** EXAMPLE OF SUCCESSFUL AND UNSUCCESSFUL CLASP OF RANDOMLY ALIGNED MEMS GRIPPERS ON A COMMERCIALLY PRODUCED FABRIC MESH

*3.2 Identifying Colored Intersections*

All the three algorithms work with the binary equivalent of the image as shown in Figure 8. Identifying colored intersections in MATLAB among the identified fiber crossings is a two-step process, wherein we can either employ the Hough line transform algorithm or binary image analysis to filter the pixel coordinates of the intersections. From the original image, we can obtain the indexed image and the color map that quantifies each pixel with RBG (Red-Blue Green) coordinates. [12] The colored intersection pixels have unique RGB values, for example greater value on Red compared to other intersection pixels in the case of our test sample. Colored pattern matching algorithm implemented in Vision Assistant-LabVIEW (National Instruments, Inc.), to achieve the same. [11]

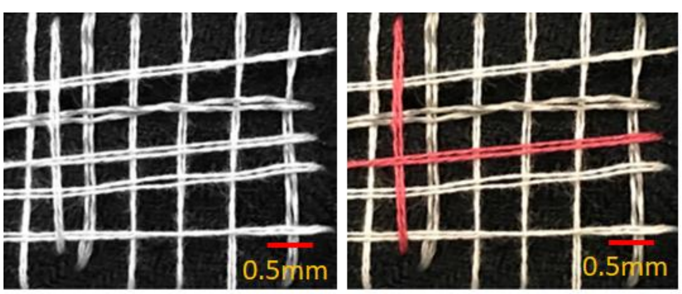


**FIGURE 9:** TEST SAMPLE LEFT: BLACK/WHITE. RIGHT: ORIGINAL IMAGE.

*3.3 Results from the three algorithms*

From Table 1, it is observed that compared to the binary image analysis and the pattern matching algorithm, the Hough line transform algorithm has the lowest accuracy since it identifies fiber strands as near-vertical lines and horizontal lines with 10-degree tolerance. Thereby a single fiber may be approximated by a number of line-segments or might not even be detected as a line segment, if it is not in the tolerance angle or if it has a curved trajectory. With a greater number of fiber cross sections per unit space, there is a notable increase in percentage accuracy using the same three algorithms.

Also, the pattern matching algorithm has the fastest computation speed as it employs a pyramidal matching technique wherein using the Gaussian pyramidal function, the image as well as the reference template are sampled to a quarter of their original sizes at each pyramidal level. This step allows faster computation but works at lower resolutions.

Table 2 gives an insightful observation of the results, by comparing the algorithms over the two different samples. The three algorithms work well with higher fiber density in the fabric swatch. The Hough line transform though has lower accuracy compared to other algorithms when observed over individual samples, it works better when the fiber density is increased as is evident in it having a greater percentage increase in accuracy of 17.22% compared to other algorithms for the given samples. An obvious increase in execution time with sample 2 is predictable.

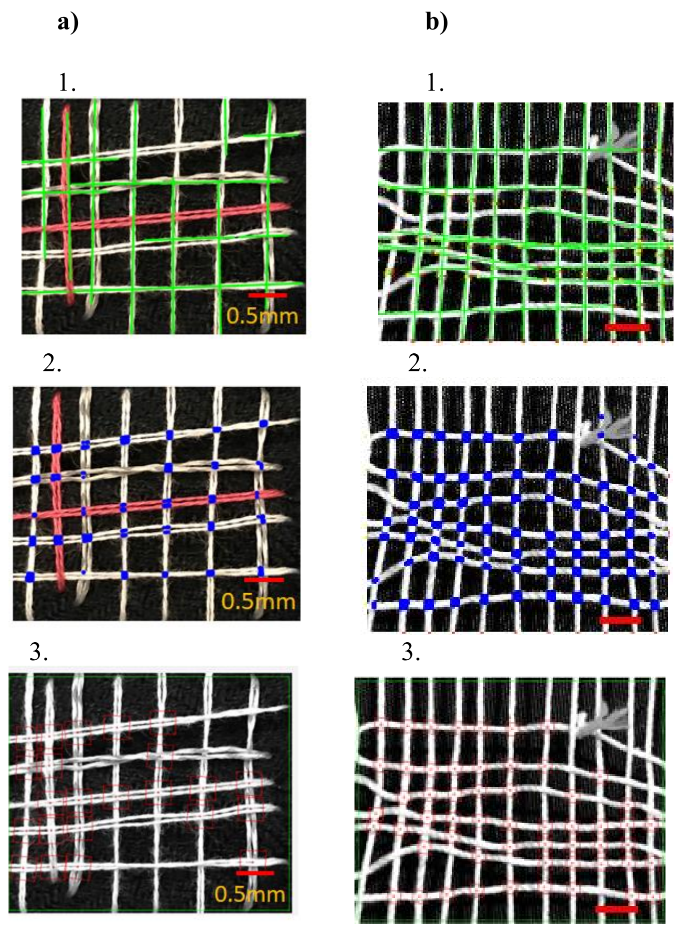


**FIGURE 10:** FIBER CROSSINGS IDENTIFIED USING 1. HOUGH LINE TRANSFORM-INTERSECTIONS OF LINE SEGMENTS 2. BINARY IMAGE ANALYSIS 3. CORRELATION VALUE PYRAMID-PATTERN MATCHING FOR COLUMN a) SAMPLE 1 COLUMN b) SAMPLE 2 (SCALE BARS 0.5 mm)

To compare the three algorithms, we looked at their consistency in successfully identifying the seven intersections in each of the five rows (Figure 10), and measured their speed and accuracy (Table 1). Another aspect of these methods is their output formats. Local pixel-neighborhood methods such as pattern matching and binary image analysis give a list of coordinates, while the Hough method returns equations of lines that often run through multiple intersections. Hough results therefore contain additional information on the network structure of the fiber junctions. While Hough can operate directly on color images, the other two algorithms are still able to get color information at each intersection location by going back into the original image. One can assign a material or a two-material junction to these intersections using a two-step process.

False positives occurred while using the Hough line transform and Binary Image Analysis.. With pattern matching there was only the issue of non-detection of some intersections (false negatives). The percentage false positives using Hough Line transform for sample 1 is 6%, while with sample 2 it is 35%. On the other hand, with binary image Analysis it was 2.5% for sample 2, while for sample 1, we didn't encounter any false negatives. There is a path to increasing the number of fiber junctions identified using the pattern matching algorithm by choosing additional appropriate reference templates.

Observing the number of fiber intersections identified per row allows a unique understanding of how the algorithms work with a straight fiber path verses a curved one, with each row corresponding to a continuous fiber path.

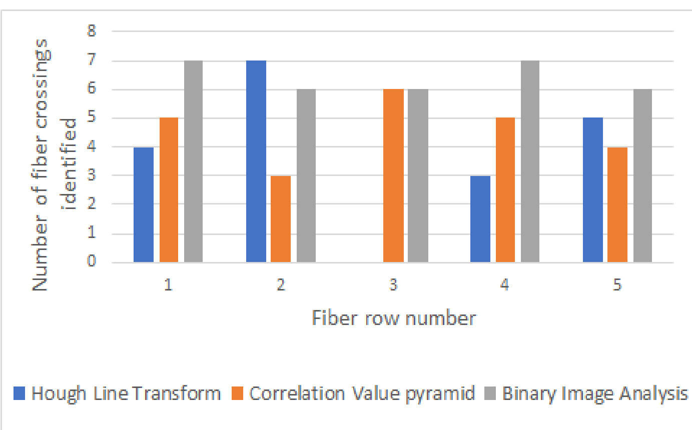


**FIGURE 11:** FIBER CROSSINGS IDENTIFIED ON EACH ROW FIBER USING THE THREE ALGORITHMS FOR SAMPLE 1

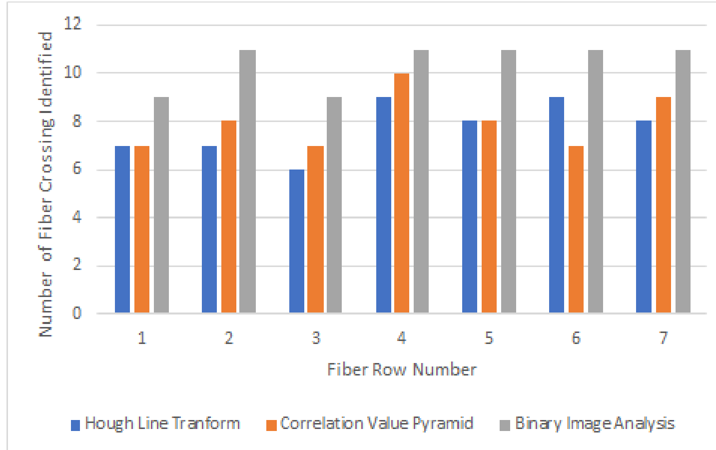


**FIGURE 12:** FIBER CROSSINGS IDENTIFIED ON EACH ROW FIBER USING THE THREE ALGORITHMS FOR SAMPLE 2

**TABLE 1:** ALGORITHMS EVALUATED OVER VARIOUS PARAMETERS

| Algorithm | Sample 1 | | Sample 2 | |
|---|---|---|---|---|
| | % Accuracy | Execution time | % Accuracy | Execution time |
| Hough Line Transform | 54.28% | 1.896 s | 63.63% | 3.219 s |
| Binary Image Analysis | 91.42% | 3.015 s | 94.8% | 2.244 s |
| Pattern matching | 65.71% | 39.02ms | 72.72% | 55.4ms |

**Table 2**: ALGORITHMS EVALUATED AMONGST THE TEST SAMPLES

| Algorithm | Between Sample 1 and Sample 2, % Change in | | Aggregate | |
|---|---|---|---|---|
| | Accuracy | Execution time | % Accuracy | Execution time |
| Hough Line Transform | 17.22% | 69.77% | 59.82% | 2.55 s |
| Binary Image Analysis | 3.69% | 34.35% | 93.75% | 2.62 s |
| Pattern matching | 10.66% | 41.97% | 69.64% | 47.21ms |

## 4. CONCLUSION

The binary image analysis algorithm correctly identified the maximum number of fiber intersections in the test sample 1, while the pattern matching algorithm exhibited highest computation speed. The comparative results were consistent with sample 2 as well, yet there was a notable percentage increase in accuracy when the fiber density is increased. This change in accuracy is significant for the Hough Line Transform Algorithm. Considering more samples with more discrepancies such as samples with varying fiber textures, orientation or uneven fiber width can demonstrate more parameters that can affect the comparative working of the algorithms. We demonstrated a MEMS gripper process that was forgiving of slight misalignment (Figure 6 and 7). The output of our algorithm was a table of x,y coordinates of the junction centers, which could feed a programmable CAD system information on how to position and lay out grippers (Figure 5) for maximum success aligning with a given piece of fabric. Fabrics have great potential as passive and active supports for electronics, but because real fabrics are irregular, such customized alignment will be important when packaging electronics on individual fabric fibers having specific functions.


## ACKNOWLEDGEMENTS

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