Automatic Measurement of Fabric Shrinkage

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NEW SOFTWARE INCREASES EFFICIENCY FOR FIBER TESTING LABORATORY

Installation of the TechWare Automatic Data Collection Software was recently completed in the Materials Evaluation Lab at the International Textile Center. Current systems online with the new software package include the Zellweger Uster AFIS, AFIS PRO, UT3 & UTR3. The system is designed to control the vast amount of information produced in the lab by automatically collecting raw data from an array of test instruments, such as strength, evenness, fiber and sliver testing machines. The software then compiles this data into useful reports and graphs including the retrieval of AFIS distribution data.

"With the new software, we are able to return test results more quickly and efficiently to our clients," said Pauline Williams, Manager of the Materials Evaluation Lab.

The system can immediately export data into Excel or other spreadsheets, and make that data available online to researchers and clients.

ITC ASSOCIATE DIRECTOR ADDS NEW DUTIES

ITC Associate Director Eric Hequet was recently named Associate Editor for the Textile Technology section of *The Journal of Cotton Science*.

In addition, Eric is the new Chairman of the Cotton Quality Measurement Conference for the Beltwide Cotton Conference.

MORE NONWOVEN EQUIPMENT INSTALLED

The ITC is now housing two nonwoven machines. Installed first, in 2001, was a Fehrer H1 Technology Needle-punch Loom, along with a Tatham Feeding Line. This has been followed, at the end of 2002, with a Phoenix Thermal Bonding Line. This machinery is being housed in cooperation with The Institute for Environmental and Human Health at Texas Tech University. It is being used in research for the Department of Defense, under the leadership of Dr. S. S. Ramkumar.

NEW CHEMICAL PROCESSING MANAGER HIRED

The ITC is pleased to announce the appointment of Dale Allen as the new Chemical Processing Manager. He replaces Gus Abdalah who retired last year.

Dale graduated from Angelo State University in San Angelo, Texas with a B.S. in Chemistry. Previously he worked for the United States Department of Agriculture as a chemist, and for a beef processing company as a supervisor in the chemical processes and tannery division.

ITC TRAVEL

- Eric Hequet to College Station, Texas to conduct his class, "Advanced Studies in Cotton Fiber," and meet with C. Wayne Smith of Texas A&M University, November 19, 2002
- Scott Irlbeck to Kansas City, MO for the National Association of Farm Broadcasters meeting, November 13-17, 2002
- Noureddine Abidi, Dean Ethridge, Eric Hequet, Scott Irlbeck, Mourad Krifa, and James Simonton to Nashville, TN for the 2003 Beltwide Cotton Conference, January 6-10, 2003

Sharing current research information and trends in the fiber and textile industries.

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AUTOMATIC MEASUREMENT OF FABRIC SHRINKAGE

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INTRODUCTION

Dimensional change of fabrics, especially due to repeated laundering, is a critical attribute and, hence, its accurate quantification is a major concern for all sectors of the textile industry. Currently, the assessment of fabric dimensional changes (specifically, shrinkage) in textile laboratories all over the world is governed by the AATCC Test Method 135.[1] This method prescribes the preparation, marking, and measurement rules that are to be followed by laboratory technicians. However, because of the very involvement of technicians, especially in the measurement stage, assessment of fabric shrinkage in this manner leads to subjective, sometimes inaccurate, and non-repeatable results.

These problems have indeed been known for over quarter of a century, and there have even been attempts to remedy them by automating the measurement process.[2,3] Despite such efforts, however, the presented system, owing to its customized image-processing algorithm, is the only known technology that has been shown to successfully assess fabric shrinkage without regard to: (1) changes in the texture, size or the color of the swatches, (2) changes in the benchmark number, color, or disposition, (3) changes in the fabric contrast due to scanning or laundering, (4) presence of noise, or (5) rotation of the swatches during the scanning process. Furthermore, the proposed system accomplishes its tasks using inexpensive hardware components that are readily available in any textile laboratory.

In the next two sections, the details of this system, together with the results of its application to a variety of fabric specimens are discussed.

SYSTEM DESCRIPTION

Hardware Requirements

The developed system may be described in terms of its hardware and software components. As mentioned previously, the former components consist of items that may be found in many of today's textile laboratories. These include a PC and a desktop color scanner or a color digital camera. The scanner may be used to obtain digital images of smaller samples (i.e., 20 cm or less), while the camera has to be used for larger samples. In either case, the images are expected to have a resolution of 30-40 pixels/cm and to be cropped to include only the swatches.[4] Once the images are transferred to the PC and saved on the hard disk, the user may invoke the software module to process the images (i.e., to detect the location of the benchmarks and to report the distance between them). In what follows, the means by which this detection and reporting are accomplished will be discussed.

Image Processing Algorithm

A software code has been developed with Microsoft Visual C++ that reads in the color images from the scanner (or the digital camera), detects the locations of the benchmarks, and reports the distance between them. This code implements a custom image-processing algorithm, which consists of the following five major steps.

Regions of Interest Identification

The first step after reading the color image into the PC memory is to identify a number of regions of interest (ROI). This is accomplished by the placement of one rectangular bounding box per benchmark (for a total of 3 or 4), around the area of the image where the benchmark is likely to be present, (**Fig. 1**). All subsequent processing is performed within these ROI only. It should be noted that this up-front selection of the ROI is aimed at handling fabrics marked with any number of benchmarks and with any predefined disposition as well as reducing the execution time of the algorithm.

Fabric Texture and Benchmark Accentuation

The main objective in the second step is to attenuate the background fabric texture and to simultaneously accentuate the benchmarks (i.e., increase the contrast of the marks). This is accomplished in two stages. First, a low-pass filter is applied by convolving the ROI with a 3´3 kernel whose weights are all equal to one. Essentially, this filter performs a simple neighborhood averaging on the image. In the second stage, the Nagao filter[5] is applied to the ROI, which further smoothes the image, while preserving the image edges. For each pixel in the image, this filter first finds the direction of least variance among nine possible directions and then performs an averaging operation in that direction. The result is an image that looks

Fig. 1 a) Input color image with four benchmarks as produced by the scanner.

a)

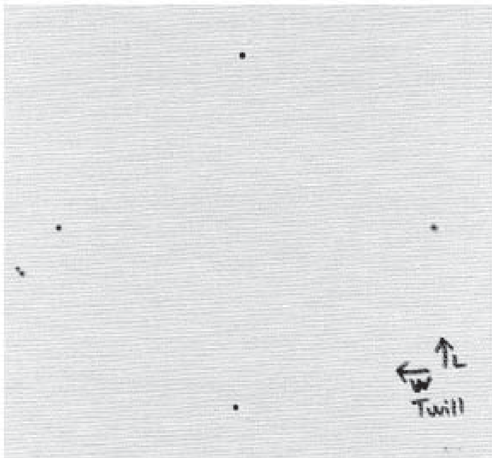
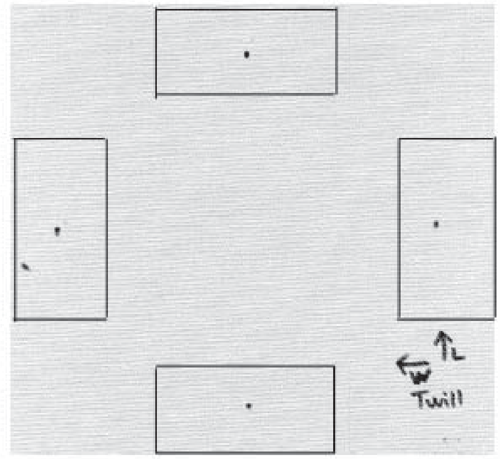


Fig. 1 b) Four regions of interest are identified automatically as rectangular bounding boxes.

b)



somewhat blotchy, primarily because the variances within homogeneous regions (e.g., those within benchmarks) decrease, while the variances within heterogeneous areas (e.g., those containing both a benchmark and the background fabric) increase. Another very important impact of the Nagao filter is that it eliminates small, inter-benchmark color variations. Images of **Fig. 2** clearly demonstrate the efficacy of this step in accentuating the benchmarks, while attenuating the background.

Color Image Splitting

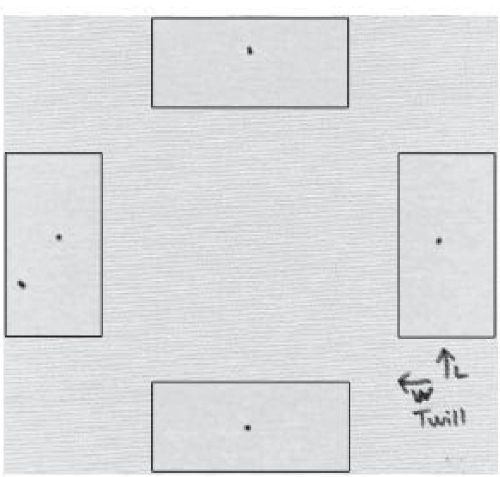
In the third step, the resultant color image is split into its red, green, and blue channels, and all subsequent operations are performed on all of these components individually. This is crucial, because having no prior knowledge about the color of the fabric or that of the marks forces us to treat the information in each of these channels equally. The lack of this prior knowledge also means that a grayscale image may not be used in lieu of the color image, as an optimal combination of the three channels into one would not be possible.

Segmented Benchmarks

In the forth step of the algorithm, the benchmarks are segmented from the attenuated background. This is accomplished by applying the local variance operator to the ROI of the output image from the previous step (i.e., each of the three color components). This operation simply replaces the center pixel in a 3x3 neighborhood with the intensity variance

Fig. 2 a) Output of the second step when the image in Fig. 1b is used as the input. b) The top graph indicates the intensity profile of a line that extends through the right benchmark in the image of Fig. 1a. The bottom graph indicates the same information for the image in (a). Note the efficacy of the two filtering operation in pulling out the benchmark from the background.

a)



b)

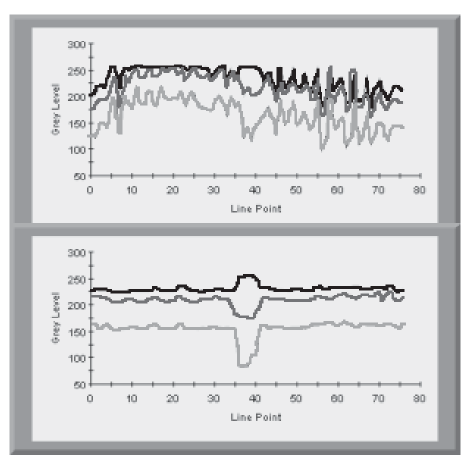
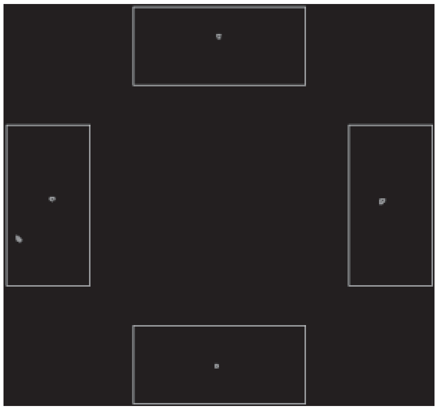
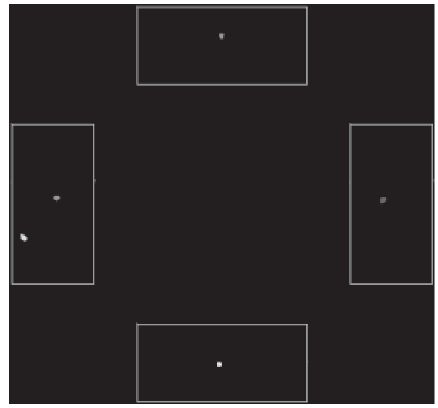


Fig. 3 a) Output of the local variance and the global thresholding operations. b) Output of the morphological closing and the blob analysis techniques, indicating the detection of the benchmarks, as well as a noise element within the left ROI. It should be noted that the displayed results are from one of the three color channels that are produced in the third step. The other two channels are treated in exactly the same fashion.

a)



b)



(second central moment) of that neighborhood. Utilization of this operator may easily be justified by considering the curves of the bottom graph in **Fig. 2(b)**. One can see how for these curves, the local variance filter (or its 1-D counterpart, to be exact) will produce large responses within those neighborhoods that contain both the benchmark and the background and small responses within all other neighborhoods. Following this operation, the image is binarized with the application of a global threshold, *T*. The optimal value for this threshold is computed adaptively for each input image in a manner that will be described later in this section. The obtained blobs from this binarization process are subsequently subjected to a morphological closing filter and then identified as connected components using a standard, blob analysis technique.[6] Hence, the output image in the forth step consists of a collection of identified blobs that potentially include the benchmarks, in addition to other extraneous elements; see **Fig. 3**.

Classification

The fifth and final step in this algorithm is the classification step. Here, relevant features are measured from the obtained blobs to determine the presence or absence of the benchmarks. These features include the size, color, and position attributes. Once these features are computed for each of the detected blobs, a rule-based classification technique determines the presence of the benchmarks in the following manner. First, the size feature is used to eliminate blobs that are too small or too large. *A priori* information about the size of the marks and the resolution of the digital images are used to set the appropriate size thresholds. Next the color within each blob (measured from the original images using the blobs as masks) is compared to that from the other blobs. Because it is known that benchmarks share the same color, only the blobs with similar colors are retained. Finally, the dispositions of the remaining blobs are checked relative to one another to ensure that the prescribed formation (e.g., cross or L-shaped) is achieved. Of course, small deviations from the known formation are tolerated to account for small errors in the placement of the marks by the technicians, in the displacement of the marks during the laundering process, or the minute rotation of the samples during swatch digitization. The reader should be reminded that the above-mentioned procedure is applied to the groups of blobs obtained from each of the three color channels. If, at the end of this step, no benchmarks are found, the procedure terminates gracefully, indicating the test conditions that led to this failure (e.g., marks are too large, or marks have inconsistent colors). Such feedback will assist the technicians to better prepare the samples for future cases.

Global Threshold Value

Let us now turn our attention to the adaptive determination of the global threshold value, T. Because the aforementioned steps are computationally inexpensive, one can afford to search for the optimal value of T (for a given input image) exhaustively. This means that the process begins with a high value for T, initially. If no benchmarks are found at the end of the fifth step, the value of T is lowered by a prescribed value and the intermediate operations are repeated once more. It turns out that such adaptive determination of the global threshold value is necessary only in the rare cases where, due to laundering or digitization conditions, the color contrast between the fabric and the benchmarks is severely and adversely affected. Images of **Fig. 4** demonstrate the output of this detection scheme on samples both before and after laundering.

As is observed, the same algorithm is used to detect the benchmarks in both pre-wash and after-wash samples. The distances between the two pairs of marks are reported **(Fig. 5)** and logged into an ASCII file, which may then be imported into a spreadsheet program for shrinkage calculations and further analysis.

Fig. 5 Screen capture showing the processed image and the obtained results.

EXPERIMENTAL

Materials

As a preliminary case study, the system was tested on 54 fabrics. The fabrics were of different types including: 100% cotton, cotton/polyester, cotton/wool, cotton/mohair, polyester/rayon, and wool; various constructions including: fleece, twill, jersey, oxford, and pique; and different colors including: white, beige, yellow, light blue, dark blue, and dark green.

Methods

To get a range of shrinkage percentages, three different cleaning technologies were used to wash the samples.

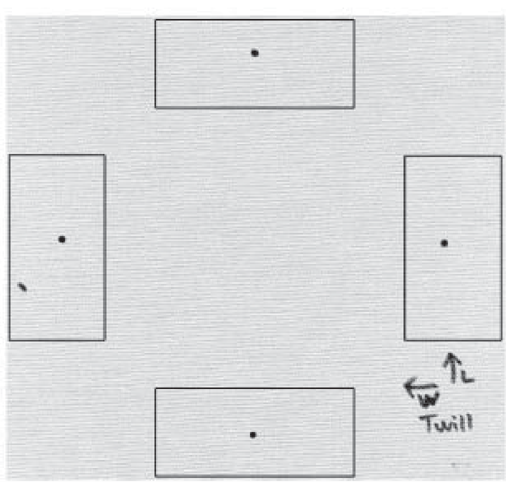
In one cleaning technology, 16 samples were washed using regular home laundering technology with three cycles washing/drying (AATCC Test Method 135 washing and drying conditions: permanent press; washing temperature, 60^{o}C; and drying procedure, tumble dry).

In another cleaning technology, 16 samples were washed using the Quickwash technology (AATCC Test Method 187 washing and drying conditions: 1 wash cycle; wash time, 165 sec; 3 rinse/dry cycles; rinse agitate time, 45 sec; spin time, 35 sec; wash temperature, 60^{o}C; and dry time, 240 sec).

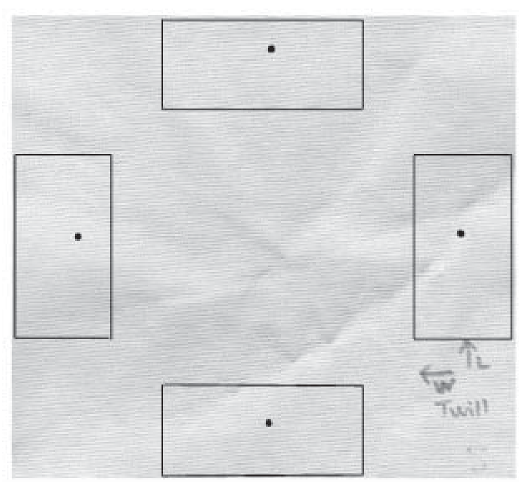
In the final cleaning technology, 22 samples were drycleaned with industrial equipment. For all samples, four replications were performed on Quickwash-size specimens (19 cm x 19 cm), and the specimens were marked with 12.5-cm benchmark distances.

Fig. 4 a) Final output of the algorithm, indicating the locations of the detected benchmarks and the distance between each pair as 12.73 cm in either direction. b) Results from the algorithm as applied to the same sample after laundering. Detected benchmarks are once again indicated and their distances are reported as 12.63 cm in the *x*-direction and 12.53 cm in the *y*-direction.

a)



b)



RESULTS

Figs. 6 – 9 and **Table I** show the results. In all cases, the developed algorithm successfully detects the benchmarks, with the computed dimensional changes and the manual measurements (in both the warp and filling directions) possessing a nearly perfect linear correlation. It is observed that on average, in the warp direction, TTU software produces a slightly higher shrinkage value. For example, at 10% shrinkage (human reading) TTU algorithm gives 10.02% shrinkage. Also, on average, in the fill direction, TTU software produces a slightly lower shrinkage value. For example, at 2% shrinkage (human reading), TTU algorithm gives 1.65% shrinkage.

In addition to the experiment described above, the proposed algorithm has undergone extensive testing in the laboratories of the International Textile Center and Cotton Incorporated.[7] The resulting intra- and inter-laboratory studies have further validated the accuracy and the repeatability of the proposed methodology.

Fig. 6 Shrinkage in the warp direction: human vs. TTU software for individual measurements.

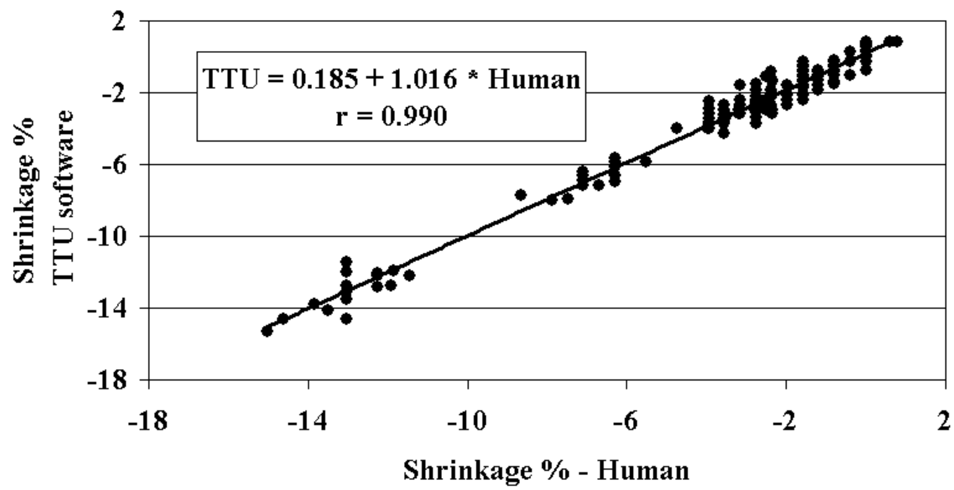
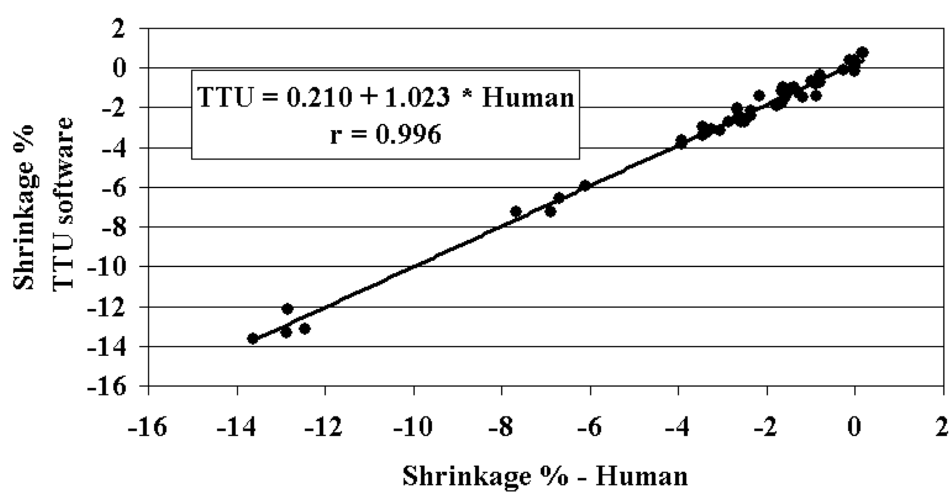


Fig. 7 Shrinkage in the warp direction: Human vs. TTU software for averages of four replications.



CONCLUSIONS AND FUTURE WORK

A vision system for the automatic quantification of fabric shrinkage has been implemented and tested. To-date results indicate an excellent correlation between the shrinkage measurements as obtained by the proposed system and those obtained by experienced technicians. Future works in this area will include the ability to handle printed fabrics and, more importantly, the addition of automatic quantification of fabric smoothness.

Fig. 8 Shrinkage in the filling direction: Human vs. TTU software for individual measurements.

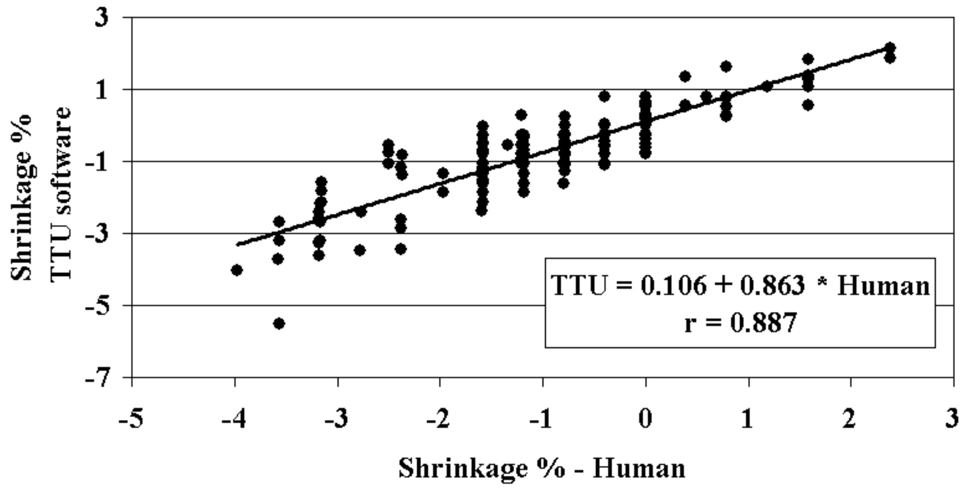


Fig. 9 Shrinkage in the filling direction: Human vs. TTU software for averages of four replications.

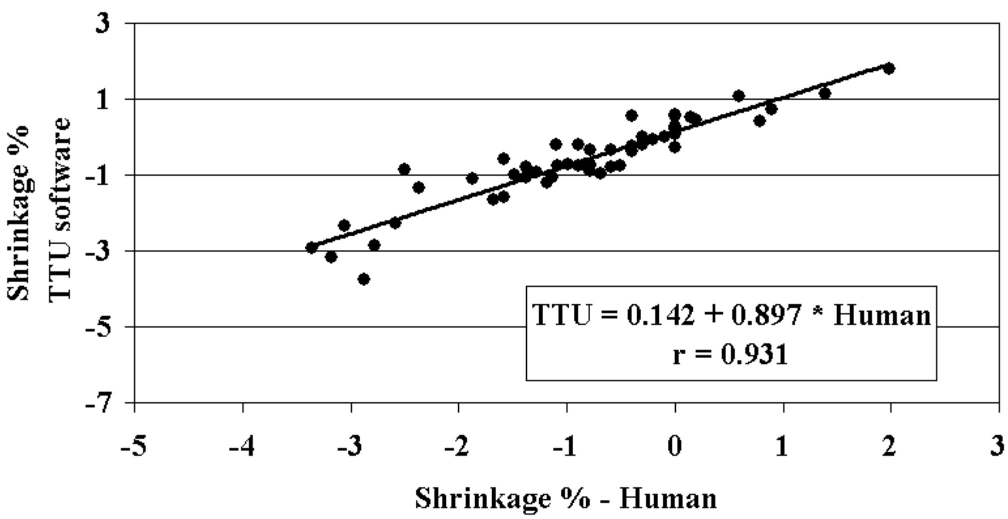


Table 1 Statistics on the Regression Lines Human vs. TTU Software

	Value	Std. Err	T Test	Prob.	-95% Cnf. Lmt.	+95% Cnf. Lmt.
Warp Indiv.						
Intercept	0.1854	0.04461	4.15	0.00005	0.0975	0.2734
Slope	1.0155	0.00996	101.92	0.00001	0.9959	1.0352
Warp Avg.						
Intercept	0.2096	0.5440	3.85	0.00032	0.1004	0.3187
Slope	1.0219	0.1233	82.86	0.00001	0.9972	1.0467
Filling Indiv.						
Intercept	0.1064	0.0448	2.37	0.01848	0.0181	0.1948
Slope	0.8627	0.0311	27.72	0.00001	0.8014	0.9241
Filling Avg.						
Intercept	0.1419	0.0677	2.09	0.04107	0.0060	0.2778
Slope	0.8965	0.0486	18.45	0.00001	0.7990	0.9941

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