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AUTOMATED GARMENT MANUFACTURING SYSTEM USING NOVEL SENSING AND ACTUATION

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ABSTRACT

Attempts to automate the sewing process of garment manufacturing have employed substitutes for human guidance of fabric into somewhat conventional sewing machines. A new approach has been proposed and partially verified in prototype form. It consists of several subsystems responsible for 1) gross fabric motion, 2) precision detection of the fabric location and 3) exact placement of the needle in the fabric. Gross motion employs steerable rollers capable of moving the fabric. Fine fabric motion employs vision sensing technology to count threads in the fabric. Exact placement employs servo controlled dogs for moving the fabric to exactly place the needle. This paper will explain the concept and the extent of verification of its realization.

INTRODUCTION

Clothing is one of the three basic necessities of human life and a means of personal expression. As such, clothing or garment manufacturing is one of the oldest and largest industries in the world. However, unlike other mass industries such as the automobile industry, the apparel industry is primarily supported by a manual production line. This paper proposes a system of automation which diverges from previous attempts in several ways, most notably in the immediate objective of the process and also the means of achieving it. The objective becomes placement of each stitch between the correct threads of the warp and weft (fill) of the component pieces of fabric, to be achieved by novel sensing and material handling devices. If this can be achieved, the resulting garment will have the proper shape when draped over the wearer's body.

The need for automation in garment manufacturing has been recognized by many since the early 1980s and is discussed comprehensively by Byrne [1] and summarized here. During the 1980s, millions of dollars were spent on apparel industry research in the United States, Japan and industrialized Europe.

A joint $55 million program between the Ministry of International Trade and Industry (MITI) and industry, called the TRAAS program, was started in 1982. The ultimate goal of the program was to automate the garment manufacturing process from start, with a roll of fabric, to finish, with a complete, inspected garment. While the project claimed to be successful, and did demonstrate a method to produce tailored women's jackets, it failed to compete with traditional methodologies.

Draper Laboratories in the U.S. was provided with $25 million of support from the government and industry with the goal of automating parts of the sewing process, beginning with setting a sleeve into a coat and then moving to automated seaming. In Europe, the BRITE project put millions of dollars towards automated sewing. Neither program resulted in successfully automating the entire process, although some minor gains were made.

CURRENT GARMENT MANUFACTURING SYSTEMS

Conventional Industrial Sewing Machines

Current industrial sewing is done mostly by hand with some processes being semi-autonomous. Cutting stacks of fabric, for example, is readily performed by NC machines, and pockets can be automatically sewn. The primary tool for the core process is the standard sewing machine, partially shown in Fig. 1. The important components with regard to this paper are the needle, needle bar, presser foot, feed dog, and the bobbin. These parts are the essential components directly involved in fabric handling and actually making the stitch.

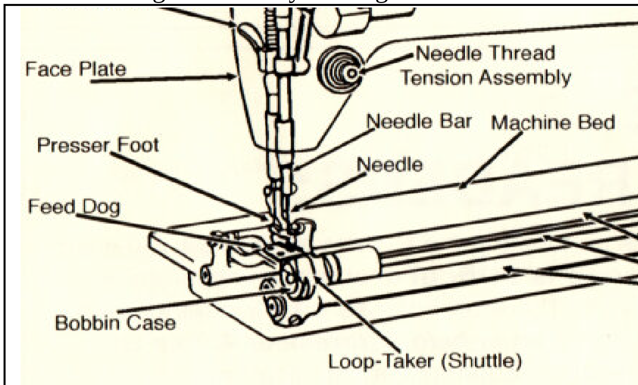


Figure 1: Standard sewing machine. [2]

The way in which a sewing machine makes a stitch is quite simple. While the needle is above the fabric, the dog feeds the fabric by pushing the fabric up against the presser foot and pulling it underneath the sewing needle. As the dog completes this motion, it begins to move down, and the needle also moves down. In the next step, the dog continues to move down and disengages the fabric. The needle penetrates the fabric, which is kept taut by the presser foot. The needle creates the stitch, called a lock stitch, using the bobbin, which holds a separate roll of thread. The needle is lifted back through the fabric, completing the stitch and tightening it as it continues to move above the fabric. As the needle is lifted, the dog is also brought up once again to advance the fabric for the next stitch.

A typical garment is composed of many parts. For example, a pair of jeans has 11 different components, with 22-24 fabric pieces in all. Due to the wide variety of parts and processes that must be carried out to assemble the parts, a flexible system that mimics the capabilities of a standard sewing machine, but that is automated, is desirable. Also, fashion, personal preferences and sizes result in an enormous number of variations even for a “standard” item. Therefore, most attempts at automating the sewing process have started with the current sewing machine and have attempted to augment the device in such a way as to replace the operator.

Prior Research Results

Early research efforts at the university level focused on control of fabric through a standard industrial sewing machine. One of the earliest attempts was by Frank Paul at Clemson University [2]. His system used machine vision to detect the edge of a piece of fabric and then plan a seam path at an offset to that edge. Difficulties arose due to outgoing filaments, inhomogeneous cuts, and wrinkles in the fabric. In addition, the project dealt only with manipulating a single piece of fabric and ignored the joining of multiple pieces. Finally, the results showed the need for real-time feedback during the sewing process.

David Gershon, at the Weizmann Institute of Science in Israel, extended the work begun at Clemson [3]. Gershon used a similar setup with a traditional industrial sewing machine and industrial robotic manipulator. However, he added real-time feedback and control. He decomposed the sewing process into four tasks: contour tracking, tension control, robot feed control, and sewing. To account for error and to maintain proper tension in the fabric, a separate control loop was used to maintain the tension in the fabric based on a force sensor in the end effector.

In maintaining proper fabric tension, tension measurement has been used to detect error in the feed rate of the robot relative to the dogs. The objective of the controller was to prevent the fabric from buckling due to compression or tension, which resulted in a poor quality seam. Tension measurement has not proven to be a method that is robust enough, given the wide range of fabric properties.

To fix problems associated with tension control and difficulties arising from the range of fabric properties, fuzzy logic and neuro-controllers were applied to a similar system by Panagiotis Koustoumpardis and Nikos Aspragathos [4]. The results did show improved robustness over previous work, but they still did not address the issue of attaching two pieces of fabric together; instead, it focused on the control of a single piece of fabric.

THE PROPOSED SYSTEM

Overview

To sew two pieces of fabric together, a number of processes must be coordinated. First, the individual sheets of fabric must be transported to the sewing table and placed flat on the table. Next, the two plies must be aligned properly and moved to the sewing head. The paired pieces are then fed through the sewing machine and sewn together. While this is occurring, the sheets must maintain proper alignment with respect to the needle and with respect to each other and must be fed at the proper rate and maintained at the proper tension. It is important to note that these requirements are for each sheet of fabric individually. At the end of the seam, the seam must be serged to complete the seam and to prevent it from coming undone. Finally, the sewing thread must be cut and the finished piece must be transported to the next stage of the process.

In order to efficiently and reliably complete these varied tasks, an integrated system using multiple types of sensors and actuators is proposed as summarized below.

An overhead pick-and-place robot with a special end effector is used to pull individual plies of fabric from a stack of pre-cut fabric pieces. Much research has been done focusing on developing a unique end effector that will allow a robotic arm to pick up a single piece of fabric at a time [5-9]. Because these components are fairly conventional, they will not be further described here.

An array of small, inexpensive “budgers” provides a useful method for transporting the fabric to the sewing head while ensuring that it lays flat and in the correct orientation. Each budger consists of a steered ball driven by two motors to rotate the ball in two perpendicular axes. Traction between the fabric and the ball is enhanced by a slight vacuum drawing a flow of air through the fabric via a series of holes in the ball.

At the sewing head, the actuation method is an adaptation of the current sewing machine feed mechanism. Currently a sewing machine uses a feed dog to move the fabric through the sewing head relying on the operator to maintain the fabric orientation and keep up with the feed rate, also operator-controlled via a foot pedal. Previous attempts at automated sewing used the sewing dogs on a standard sewing machine and had a robot perform exactly the operations a human operator would perform.

This project endeavors to replace the standard sewing dogs and human operator with servo-controlled dogs. By using the feed dog mechanism as the method by which to control the fabric, the difficulties of fabric feed rate, tension control, and fabric position control can all be more adequately addressed. The budgers provide the large fabric motions that the human operator would normally provide and hence coordination between budgers and dogs will be necessary.

For the actuators at the sewing head to achieve high position accuracy, sensing must be precise because it determines the stitch position and stitch length. A major hurdle in using machine vision to provide position feedback using vision has been the errors introduced by variability of the edges of fabric due to outgoing filaments and deformation of the cloth off of the table surface [10]. To alleviate this issue, a new vision technique is proposed and has been demonstrated as a prototype to provide fabric position information by tracking individual threads in the fabric. Therefore, the position of the fabric is to be measured in threads rather than millimeters or inches. In the previous research described above, fabric position is based on the shape of the fabric relative to a global coordinate system. As such, any fabric deformation results in position error. Using the fabric's threads for position detection at the point of the needle's entry into the fabric avoids errors. It also avoids problems of noise in the fabric edge. No previous work has attempted to track fabric threads to measure position and orientation. However, a number of papers have been written on using vision to detect thread-based information on fabric, such as fabric defects or fabric weave patterns [11-16].

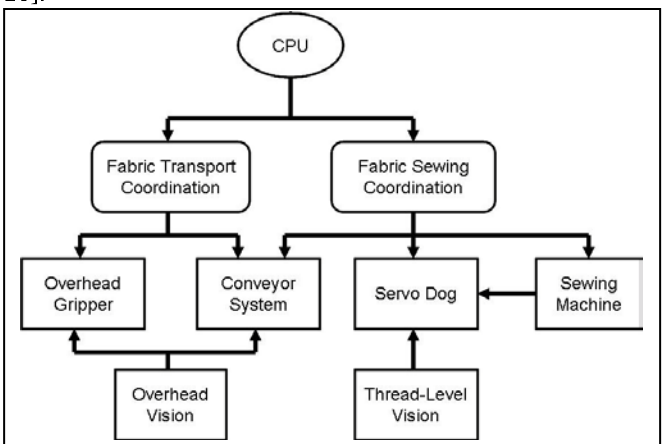


Figure 2: Block diagram of control hierarchy.

Integrating the various components of the system requires a control hierarchy such as the one shown in Fig. 2.

Budger Design and Test

Electric motors (currently both stepping motors and DC motors have been tried) spin the perforated ball and control the angle of the spinning axis as shown in Figure 3. A slight vacuum is critical to maintaining the normal force between the fabric and the ball high enough to move the fabric. The vacuum pulls air through the holes created in the ball, as seen in Figure 3. The holes pass through the center of the ball, allowing air to flow through the fabric to the vacuum chamber. The budgers have demonstrated effectiveness at moving and steering fabric at rates up to 160 in/sec, but with some slip, necessitating vision feedback control.

The motors that control the budgers must have position sensors in order to follow a given trajectory. However, due to the nonlinear mechanical properties and varieties of fabric, and noticeable slip between the budgers and the fabric, position feedback of the fabric itself is necessary. The vision system will observe the position, alignment, and shape of the fabric to ensure that the fabric remains aligned. This is one of two vision systems and is described below in greater detail. More precise sensing at the thread level will occur at the sewing head.

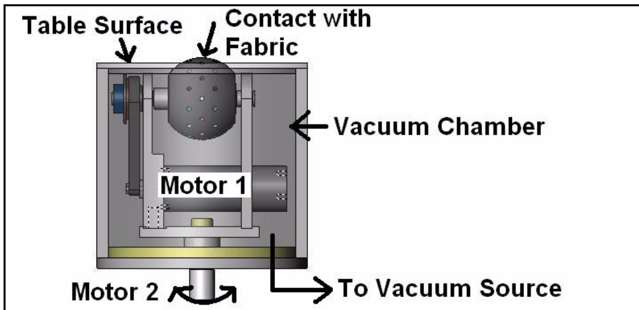
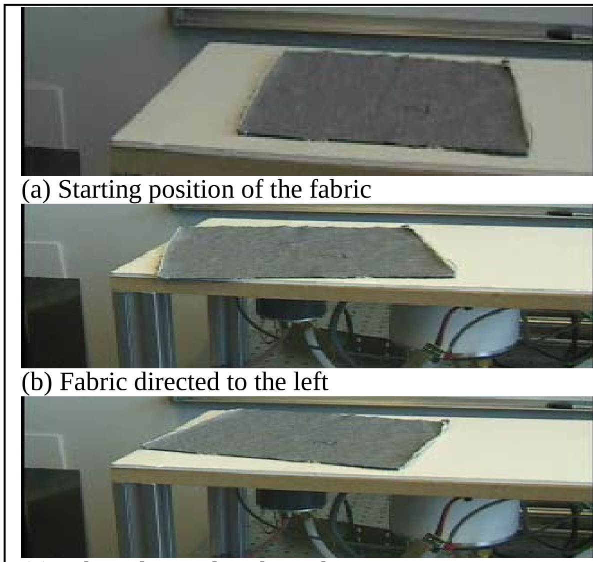


Figure 3: Budger for gross fabric motion.

The ability of a single budger to steer is illustrated in Figure 4. The square of cloth begins stationary in the first frame and is moved forward quickly, first to the left and then to the right. Coordinated action of two or more budgers can produce near arbitrary translation and rotation (including rotating in place). The coordination of two or more rollers is almost identical to the coordination of independent steering of multiple wheels on a vehicle in which the vehicle is upside down and subject to the same holonomic constraints. Driving the balls in a holonomic fashion is also feasible but complicates the construction of the budger.

Machine Vision for Budger Control

Vision for budger control has been developed by Killpack in the course of work at Georgia Tech's Robotics and Intelligent Machines (RIM) program [17]. Killpack looked at prior work in vision tracking and position estimation. Since fabric is flexible and subject to out-of-plane motion an appropriate model of modest complexity is needed. Past work in simulating or modeling cloth behavior can be largely divided into geometrical or physical techniques or a hybrid of both. Ng et al [18] summarized the initial work in this field. They explained that geometrical techniques do not consider properties of cloth but focus on appearance, especially folds and creases represented by geometrical equations. Physical techniques generally use triangular or rectangular grids with points of finite mass at the intersections. Real-time implementation of models has also been considered, for example by Meyer et al [19].



(a) Starting position of the fabric

(b) Fabric directed to the left

(c) Fabric directed to the right

Figure 4: Fabric movement by one budger.

Tracking the large motions of a piece of fabric is necessary to deliver the fabric to the sewing head accurately. It is considered acceptable to place clearly identifiable markings or fiducials on the fabric to facilitate this task, although existing features on the fabric may eliminate this need. The vision system must track these individual fiducials and estimate the position of the cloth. Estimation can be improved with a suitable model of the cloth behavior. A Kalman filter or Extended Kalman Filter (EKF) is commonly used to estimate the position of a body in the presence of noise and requires a model of the fabric. For this application, two different models for the cloth were compared. The first modeled only x, y, and theta displacements and velocities at the center of mass of the cloth. This was done by modeling the cloth as a rigid plate with a nominal mass and coefficients of friction (static and dynamic). The second model includes a two-dimensional non-rigid finite element mesh where the node positions represent the states of the cloth. At each time step, the motion of the center of mass of the cloth was still predicted. In the prediction step of the EKF the positions of the nodes are then calculated according to their relative position with respect to the center from the last time step. During the measurement update in the EKF, the nodes are allowed to move in a non-rigid fashion. The cloth to be used for this research is denim. Although for denim, the assumption of a rigid object for tracking will perhaps be sufficient, it is not general enough for other types of materials or even extreme cases where the cloth moves rapidly or non-rigidly. For this reason, both a completely rigid model and a mesh model of the cloth were considered.

The tracking process involved four distinct events of 1) initialization, 2) state prediction, 3) measurement with data association and 4) state correction. The initialization stage concerns only the initial frames of the sequence. Background subtraction could be used to identify the cloth (foreground) from the background of the conveyor system. Background subtraction and manual selection was used to identify the region of interest (ROI) for now.

The algorithm was initially implemented in Matlab and three cloth movement tests were performed. The first is the simple translation of the cloth in a single direction with one applied force in that direction. The second test is a rotation and translation of the cloth induced by a force with a moment arm. The third test is the compression and tension of the cloth from both sides causing a folding and unfolding in the middle. These tests permit us to test the limits of the current implementation and look for improvements.

The data was collected and stored and the estimation in Matlab was based on one of several alternative assumptions with corresponding of computational burden:

- no assumed model or force
- only the assumed force for the rigid model
- an assumed force and the EKF for the rigid model
- no assumed force and the EKF for the rigid model
- an assumed force and the EKF for the mesh model
- no assumed force and the EKF for the mesh model

For testing these assumptions, the cloth was moved by hand under the camera. The consequence of different processing techniques is shown in Figure 5 through Figure 8. For each frame, the predicted location of 20 feature points was measured against the manually extracted location of those feature points and we call this error the residual. The average pixel error for each frame was reported as well as the worst error. We assume that for an overhead camera setup, the image can be rectified so that it is parallel with the plane of the workspace. This would mean that pixel error reported is proportional to cloth prediction error in length units as long as the cloth remains mostly in the plane. For the rigid assumption and simple translation, error is greatly reduced by the EKF as shown comparing Figure 5 to Figure 6, where the error remains in the vicinity of 2 pixels. This is probably adequate unless the fabric is prone to buckling as is the case when the direction of motion is reversed.

Particularly challenging is the case when the cloth momentarily buckles and is then straightened out. In this case, a grid description of a flexible body gives great improvement. This difference is dramatically shown when comparing Figure 7 and Figure 8. The use of improved models is still under consideration and more extensive testing is needed to ensure that other forms of buckling are adequately considered.

While no attempt was made to achieve real-time operation in these tests, attention was given to the potential shift to real time with customized hardware and software. The speed of these experiments relative to other published data is given in Table 1. No attempt has been made to account for differences in hardware, but it indicates that the combination of hardware and software is moving encouragingly close to real time.

Thread Counting Vision System

Central to the proposed approach for garment manufacture is the ability to reliably “count threads” in the fabric cut parts. More specifically, this refers to a process of:

- continuously monitoring a small region of fabric in the immediate vicinity of a dog (which may be either cutting or sewing)

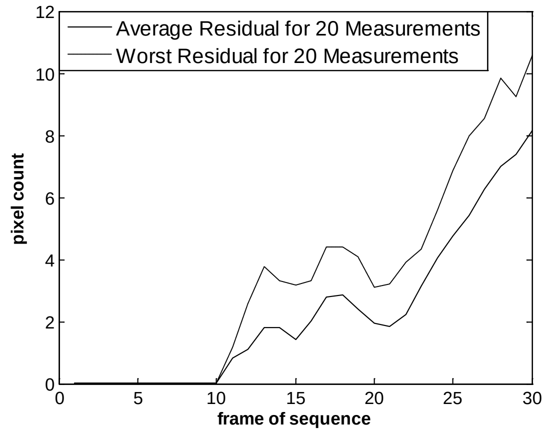


Figure 5: Magnitude of residual between measurement and prediction for force alone.

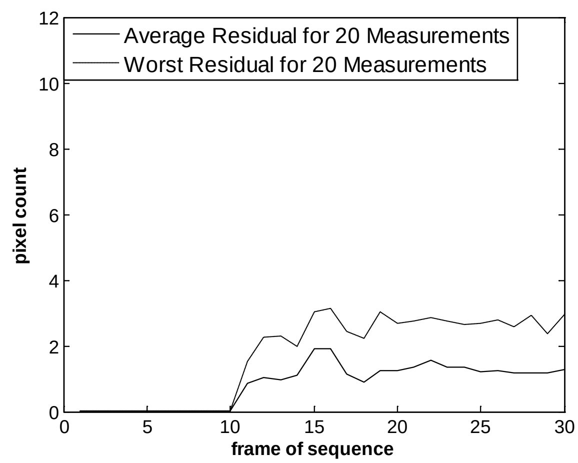


Figure 6: Magnitude of Residual for EKF with assumed force.

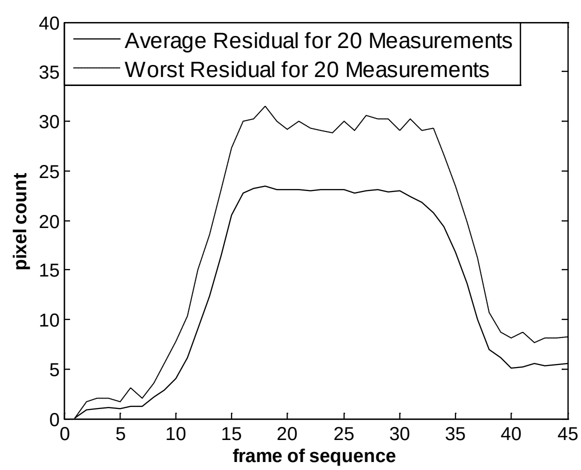


Figure 7: Residual for back and forth motion with no model.

- allowing for local deformation of that region of fabric so that the center point is kept within the proper context of the non-Euclidean thread-based coordinate system relative to an original starting point or datum, maintaining
  1. The cumulative number of warp threads that have passed the center point,
  2. The cumulative number of fill threads that have passed the center point, and
  3. The current angular orientation of the fabric.

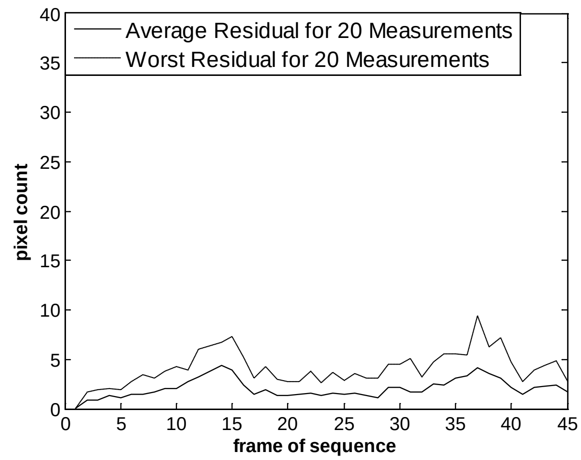


Figure 8: Residual for back and forth with EKF and mesh model.

Table 1 Processing rates by various researchers.

Authors	Rate of analyzing frames
Pritchard et al. (2003) [20]	0.0028 fps
Hasler et al. (2007) [21]	2.7E-5 fps
Hernandez et al. (2008) [22]	0.025 fps
Bradley (2008) [23]	2.78E-4 fps
Killpack et al. (2008) [17]	4 fps

Note that the cumulative count includes both positive and negative increments. The third requirement above, maintaining at least an approximate angular orientation, is key to knowing whether the passage of a thread represents warp or fill, and whether it is a positive or negative increment. A more precise estimate of angular orientation is required to rotate the dogs for closed-loop control of stitch patterns at arbitrary angles relative to warp and fill.

This thread-counting process has only recently become feasible at the speeds required for a production environment. The primary enabling technologies are very fast imaging devices and moderately priced computational hardware that allow both sensing and computation to be performed in a small unit that can be replicated numerous times throughout a production machine while still meeting cost targets. Indeed, CMOS imaging devices are now commercially available for less than $50 that are capable of exceeding the requirement of 1500 frames per second. Although strong lighting is required for such high-speed operation, it is perfectly reasonable for a controlled manufacturing environment.

The requirement of a high frame rate results from the need to recognize very small motion (less than the width of a thread) in successive frames, i.e., to satisfy the Shannon sampling theorem as it applies to the spatial frequencies of the image. This is true regardless of whether a spatial-domain approach or a frequency-domain approach is taken. In fact, a hybrid of spatial and frequency techniques has been demonstrated at this point, achieving the initial objectives. As illustrated in Figure 9, features (corners, specifically) are first extracted from raw image data. Two parallel algorithms estimate translation and rotation, respectively. Both utilize corner features resulting from a Harris corner detection algorithm [24], not only because corners are generally strong invariant features, but also because weave patterns exhibit them in abundance. A sample fabric image is shown in Figure 10, with detected corners superimposed. There is no assumption that all corners will be detected or that the same corners will appear in successive frames – only that a very large number of the same corners will appear in successive frames.

The left branch of Figure 9 is the approach used to detect fabric translation, measured at the center of the image (corresponding to the center of the dog's local coordinate system). The process is illustrated with images in Figure 11 and Figure 12. Although these are generated from simulated frames that include deliberate noise and miscorrelation, they are representative of millions of data frames which have been acquired with prototype hardware in the laboratory. In Figure 11, two successive frames have simply been compared to find the pairwise sets of nearest corners in each frame. Each set results in a vector that describes the hypothesized motion during the frame interval at that point on the fabric. Some of the correlations appear obviously incorrect in the figure however, the miscorrelated pairs can be eliminated, and a more accurate average translation can be determined, resulting in dx/dy, as shown in Figure 9. This enables not only discrete thread counting, but actually fractional thread counting. All that is required is to perform a coordinate transformation between the camera frame of reference and the fabric itself. This requires a method of estimating the fabric rotation (dTheta), shown as the right branch of Figure 9.

Actually, as Figure 12 shows, it is possible to estimate differential rotation as part of the same algorithm that computes translation. But better results, free of accumulating incremental errors, can be attained by considering the weave pattern. Whereas the dx/dy pattern is small and repeats so often as to be unrecognizable from frame to frame due to aliasing, the rotational orientation is easily recognizable in successive frames as long as differential rotation is less than 45 degrees. So, a conventional approach of taking a 2D FFT is utilized, resulting in strong peaks corresponding to the spatial frequencies of the warp and fill threads. Tracking the corresponding angular orientation of these peaks in the spatial image from one frame to the next ensures that the fabric angle is estimated correctly.

Prototypes of the vision system have been developed to demonstrate the feasibility of real-time tracking of threads. An initial prototype was developed utilizing an existing vision system. It consisted of an OP9630 camera and a Xilinx Spartan 2e FPGA. Images were collected from the camera at 15 fps and real-time tracking of the fabric was demonstrated. Following the initial prototype, additional work was performed to execute the processes at a minimum of 1500 frames per second. For this second prototype effort, a high speed CMOS camera (Photonfocus MV-1024E-40-CL), a precision lens (Fujinon CF16HA-1) and a high-speed Xilinx FPGA development board (with a Virtex 5 FPGA) were utilized. The camera was able to capture and send a 128x128 pixel image at a rate of 1500 fps to the FPGA board. The FPGA board then tracked the movement of the fabric and passed the information via USB to a PC.

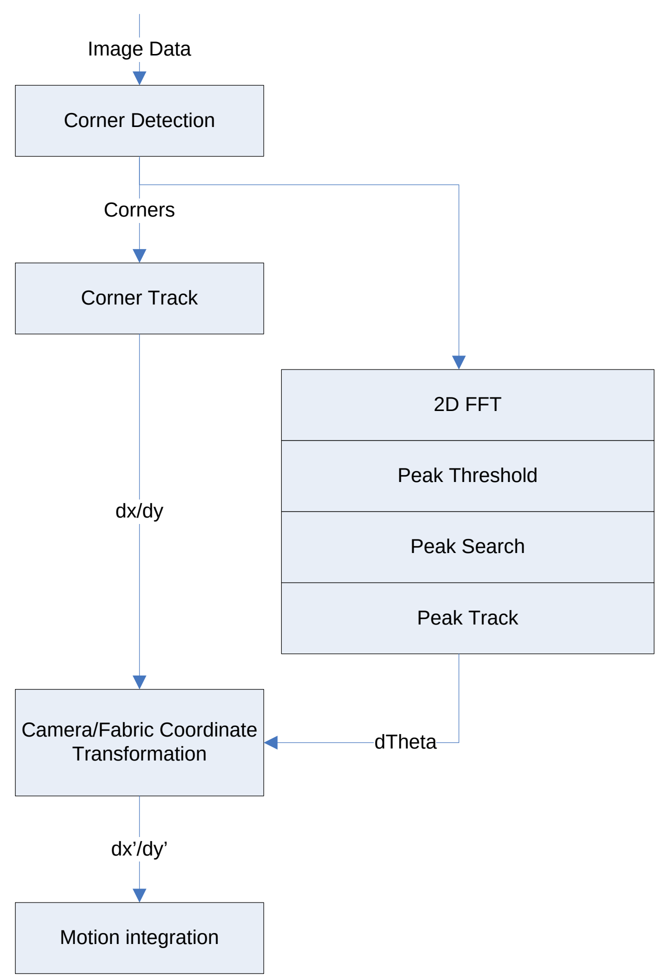


Figure 9: Thread Counting Vision algorithm.

Servo Dog Capability Development

The specifications and technology to meet them was established in work by Ryder Winck at Georgia Tech [25-26]. The maximum travel of a servo dog needs to be only the distance of the longest stitch length anticipated for the application. Typical sewing speeds for non-autonomous sewing can be up to 5,000 stitches per minute, which is about 80 stitches per second. Assuming an average stitch length of approximately 2 millimeters, the servo actuators must be able to accelerate up to about 23 g's or 225 m/s^2 in order to compete with the speed of the current manual sewing process.

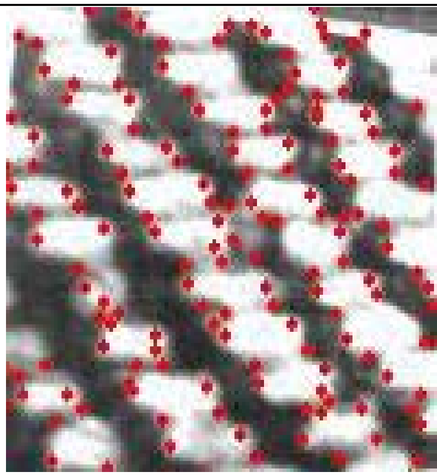


Figure 10: Image of blue denim, with features resulting from a Harris corner detector superimposed.

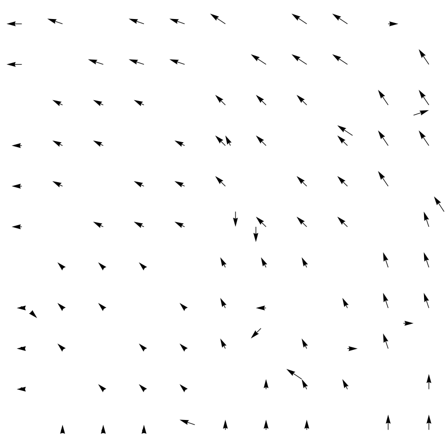


Figure 11: The result of associating the nearest corners of two successive frames of corner features, where corner translation is shown with a vector.

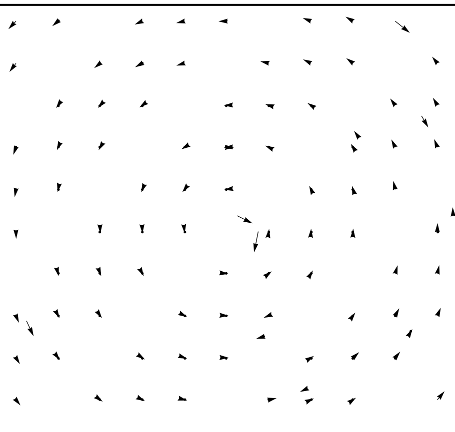


Figure 12: The result of subtracting the average dx/dy translation, leaving only the rotational component and some obviously miscorrelated corner features (which can optionally be removed in a second pass of the algorithm).

The accuracy of the dog's motion must be proportional to the length of travel because large variations in stitch length and stitch position cause unacceptably poor seam quality. In other words, the position accuracy should be on the order of fractions of a millimeter.

The servo dogs are located in front of the needle, unlike the standard feed dog, in order to be able to orient the fabric properly before the fabric reaches the needle. Therefore, they no longer will have the presser foot to push against and instead will be mounted above the fabric and push down against the surface of the table.

Figure 13 depicts the six different degrees of freedom fabric might exhibit on the surface of constraint. If one can assume that, with respect to the dogs, the stretch and shear are negligible and that the fabric only needs to be able to orient to the sewing head and feed into it, then only the two degrees of freedom described above (forward/back and rotate) are necessary. However, because the fabric has the potential to buckle and stretch at the sewing head, it is likely that the three degrees of freedom associated with fabric deformation will also need to be controlled.

In addition to multiple degrees of freedom, the servo dogs must be able to control two sheets of fabric, which overcomes a significant deficiency in previous designs for automated sewing. A better solution is to separate the two sheets with a surface in between them, such as a thin steel plate, as shown in Figure 15, and have servo dogs above and below the plate, one set of two dogs for each ply.

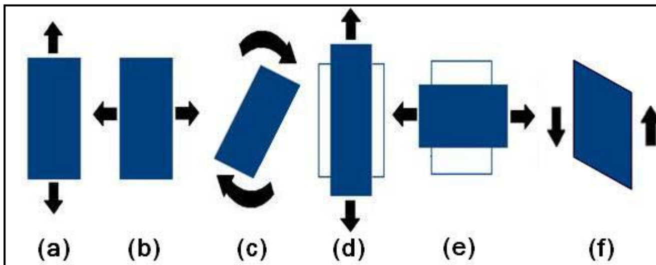


Figure 13: Fabric on a surface has six degrees of freedom: two directions of translation (a) (b), one direction of rotation (c), two directions of stretch (d) (e) and one direction of shear (f).

To obtain the high accelerations required for the servo dogs to keep up with the sewing machine, an average DC or stepper motor is insufficient. Instead, voice coil motors are used. In general, voice coil motors have a low force output per motor mass and so it is beneficial to mount the motors apart from the moving part of the servo dog to reduce the inertia of the dogs. Therefore a cable drive system is necessary to transmit the force from the motor to the dogs. To accurately control the position of the voice coil motors, an optical linear encoder provides a precise non-contact solution.

A prototype of the proposed actuator has been developed to demonstrate the feasibility of multi-degree-of-freedom servo control at the high accelerations, accuracy and precision required. The prototype is designed to have two degrees of freedom, the minimum number of degrees of freedom for controlling a fabric sheet on a surface. The prototype uses two voice coil motors and a cable drive system to transfer power to the servo dog while allowing the motors to be mounted apart from the servo dog.

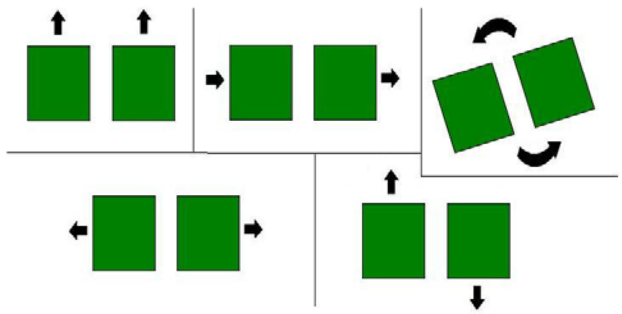


Figure 14: The blocks represent the servo-controlled dogs and the arrows show how five degrees of freedom can be controlled: translation up/back (a), translation left/right (b), rotation (c), stretch in one direction (d), and shear (e)

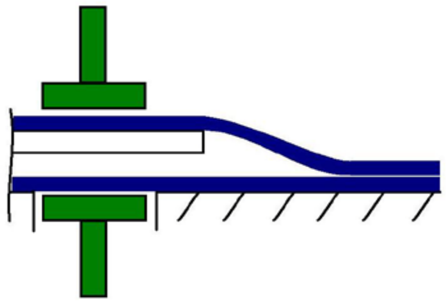


Figure 15: A thin plate separates two sheets of fabric. Each sheet is individually controlled by two manipulators although only one can be seen in this side view

The system uses linear optical encoders for position control of the voice coil motors, but the position control of the fabric itself is open loop control. Ultimately work-piece feedback would be provided by the thread counting vision system. A single dog is used to achieve both forward and reverse motion and rotation. This is sufficient for obtaining in-plane motion but cannot stretch or shear the fabric. The entire device is mounted on an industrial sewing machine that had been modified to allow for the servo dog. For out-of-plane motion, the dog is mechanically attached to the sewing needle to force proper timing between the contact of the servo dog and needle with the fabric.

The sewing machine used for the prototype is a Juki DLN-415-5 Single Needle Lockstitch Sewing Machine, shown in Figure 16, with the servo dog frame attached.

The sewing needle to dog linkage system, shown in Figure 17, mechanically connects the servo dog to the sewing needle, ensuring proper timing between the two devices. The actuator used for the prototype consists of a Gee Plus VM2618-180 voice coil motor and Renishaw RGH24Z30F00A linear optical encoder. The voice coil motor has a peak force of about 10 N and a total travel of 4 mm at a force greater than 90% of the peak force. The travel of the actuator is mechanically limited to just over 4 mm of stroke. Therefore, with a desired acceleration of 23 g's or 225 m/s^2, the total allowable moving mass is about 44 grams. The motor itself has a moving mass of 6 grams.

Figure 16: The sewing machine with prototype frame mounted.

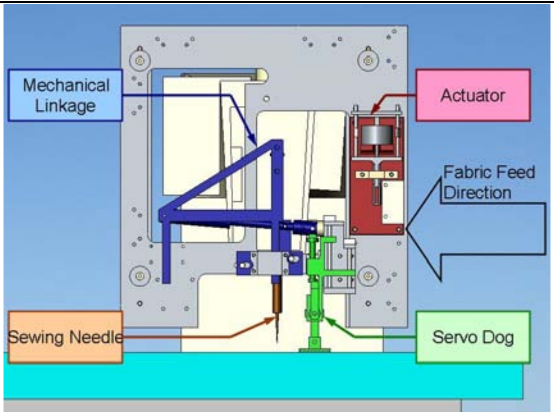


Figure 17: A CAD model of the servo dog prototype mounted on a sewing machine. The primary components of the system are highlighted.

The cable drive system shown in Figure 18 transfers power from the actuators to the mechanical dog. This permits the actuator housings to be stationary and is a lightweight method of transferring power. Because of the change in distance as the dog moves up and down, albeit small, it is necessary that the cable be flexible.

The prototype actuator has demonstrated the capability of controlling the fabric over a closed trajectory. Two test trajectories are shown below in Figure 19 and Figure 20. The control is entirely open loop with respect to the fabric position. Attempts at following a closed trajectory have confirmed the need for feedback control of the fabric position primarily to account for fabric slip at the point of contact with the actuator. This can be seen in Figure 19 where the final straight line is not at a perfect ninety-degree angle to the vertical line and in the varied lengths of each motion although the motions were programmed to be the same length.

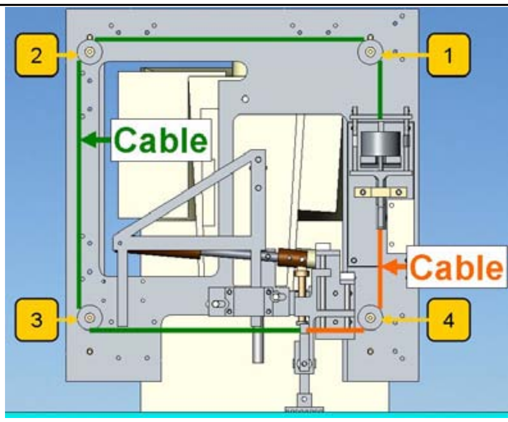


Figure 18: Two sets of four pulley wheels (one set not shown) guide the cables from the actuators to the dog.

CONCLUSIONS AND FUTURE WORK

Based on the work to date, the approach proposed seems to be technically feasible, although additional work on the thread counting vision system is needed and is underway. It also appears that the approach can be economically viable, based on other evaluations. Obviously, a fully functioning, integrated system will demand much more work and significant funding.

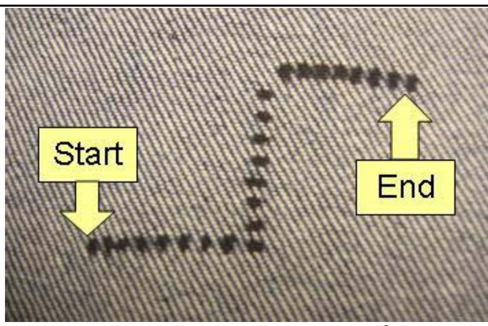


Figure 19: Trajectory showing two 90^o turns, one left and the next right.

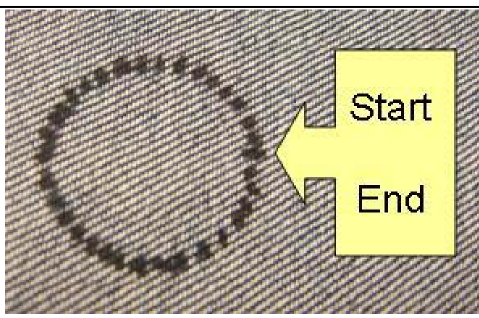


Figure 20: A circular trajectory with the endpoint being the same as the starting point.

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REFERENCES

[1] Byrne, C., 1995. "Impact of new technology in the clothing industry: outlook to 2000". Textile Outlook International, March, pp. 111-40.
[2] Torgerson, E., and Paul, F., 1988. “Vision guided robotic fabric manipulation for apparel manufacturing”. IEEE Control Systems Magazine, 8(1), February, pp. 14-20.
[3] Gershon, D., 1990. “Parallel process decomposition of a dynamic manipulation task: robotic sewing”. IEEE Transactions on Robotics and Automation, 6(3), June, pp. 357-367.
[4] Koustoumpardis, P., and Aspragathos, N., 2003. “Fuzzy logic decision mechanism combined with a neuro-controller for fabric tension in robotized sewing process”. Journal of Intelligent and Robotic Systems, 36(1), January, pp. 65-68.
[5] Kondratas, A., 2005. “Robotic gripping device for garment handling operations and its adaptive control”. Fibres and Textiles in Eastern Europe, 13(4), October, pp. 84-89.
[6] Kolluru, R., Valavanis, K., Smith, S., and Tsourveloudis, N., 2002. “An overview of the University of Louisiana robotic gripper system project”. Transactions of the Institute of Measurement and Control, 24(1), pp. 65-84.
[7] Zoumponos, G.., and Aspragathos, N., “Fuzzy logic path planning for the robotic placement of fabric on a work table”. Robotics and Computer-integrated Manufacturing, 24(2), April, pp. 174-186.
[8] Taylor, P., Monkman, G., and Taylor, G., 1988. “Electrostatic grippers for fabric handling”. Proceedings of the 1988 IEEE International Conference on Robotics and Automation, 1, April, pp. 431-433.
[9] Parker, J., Dubey, R., Paul, F., and Becker, R., 1983. “Robotic Fabric handling for automating garment manufacturing”. Transactions of the ASME. Journal of Engineering for Industry, 105(1), February, pp. 21-26.
[10] Gershon, D., and Porat, I., 1988. “Vision servo control of a robotic sewing system”. IEEE International Conference on Robotics and Automation, 5, April, pp. 1830-1835.
[11] Cho, C.S., Chung, B.M., and Park, M.J., 2005. “Development of Real-Time Vision-Based Fabric Inspection System”. IEEE Transactions on Industrial Electronics, 52(4), August, pp. 1073-1078.
[12] Goncalves, P.J., Furtado, H.A., Morato, J.P., and Goncalves, M.A., 2002. “Automatic Fabric Inspection by Machine-Vision, Applying Simple Algorithms”. Proceedings of SPIE, 4664, pp. 198-206.
[13] Huang, C.C., Liu, S.C., and Yu,W.H., 2000. “Woven Fabric Analysis by Image Processing Part I: Identification of Weave Patterns”. Textile Research Journal, 70(6), June, pp. 481-485.
[14] Kang, T.J., Kim, C.H., and Oh, K.W., 1999. “Automatic Recognition of Fabric Weave Patterns by Digital Image Analysis”. Textile Research Journal, 69(2), Feb., pp. 77-83.
[15] Millan. M.S., and Escofet, J., 1996. “Fourier-domain-based Angular Correlation for Quasiperiodic Pattern Recognition. Applications to Web Inspection”. Applied Optics, 35(31), November, pp. 6253-6260.

[16] Tincher, W.C., Daley, D., and Holcombe, W., 1993. “Detection and Removal of Fabric Defects in Apparel Production”. Report to Defense Logistics Agency, March.
[17] Killpack, Marc, “Cloth Modeling and Tracking with Future Applications for Control”, ME/CS 8750 Final Report, Georgia Institute of Technology, December, 2008.
[18] Ng, H.N. and R.L. Grimsdale. Computer graphics techniques for modeling cloth. IEEE Comp. Graphics and Applications, 16(5):28-41, 1996.
[19] Meyer, M., G. Debunne, M. Desbrun and A. Barr, Interactive animation of cloth-like objects in virtual reality, J. of Visualization and Computer Animation, 12(1):1-12, 2001.
[20] Pritchard, D. and W. Heidrich, ―Cloth Motion Capture,‖ Computer Graphics Forum, 22(3):263-271, 2003.
[21] Hasler, N., B. Rosenhahn, M. Asbach, J.R. Ohm, and H.P. Seidel, ―An analysis-by-synthesis approach to tracking of textiles, Proc. of Int. Workshop on Motion and Video Computing, 2007.
[22] Hernandez, C., G. Vogiatzis, G.J. Brostow, B. Stenger, R. Cipolla, "Non-rigid Photometric Stereo with Colored Lights," ICCV 2007, pg (1-8), October 2007.
[23] Bradley,D., T. Popa, A. Sheffer, W. Heidrich, T. Boubekeur. "Markerless Garment Capture," SIGGRAPH 2008, pg 1-8, 2008.
[24] Harris, C. and M. Stephens (1988). "A combined corner and edge detector". Proceedings of the 4th Alvey Vision Conference: pages 147-151.
[25] Winck, Ryder, “Fabric Control for Feeding into an Automated Sewing Machine”, M.S. Thesis, Georgia Institute of Technology, Atlanta, GA, May, 2009.
[26] Winck, Ryder, Steve Dickerson, Wayne Book and James Huggins, “A Novel Approach to Fabric Control for Automated Sewing,” 2009 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, Singapore, July 14-17, 2009, pp53-58.