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Intelligent Sewing: A Survey

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Abstract We review the state of the arts of intelligent sewing technologies. By intelligent sewing, we include all the sewing techniques involving robots or intelligent system. Different from conventional sewing machines that rely on human guidance or presetting parameters, intelligent sewing systems have the ability to adapt their behaviours, eg. sewing path and tension, according to different sewing contexts.

1 Introduction

1.1 Motivation

Medical sewing and industrial sewing

While robots have long been used for the mass production of sewn goods, the kind of robots seen in factories were used for automated sewing machines for simple tasks or for automatic pattern cutting. While their use decreased the time for these laborious tasks, the entire manufacturing pipeline still remained labour intensive. For fully automatic robotic sewing, there still remain many challenges before robots are able to completely replicate the complex manipulation of fabric and thread that a human is able to achieve. Robotic sewing can be found in a number of manufacturing and non-manufacturing industries: automotive, garment, footwear, furniture, and medical environments. While there has been research in improving the automation in the processes involved, current solutions are not cost effective and most still rely on human guidance or preset parameters. In this paper, we review the state-of-the-art in intelligent sewing. We classify intelligent sewing as techniques and systems that involve robots or intelligent systems that are able to adapt their behaviour to changes in the environment.

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1.2 Technical challenges

(Medical: Celia, Industrial: Bidan and Yang Hu)

Clinical solution requirements: can't control environment, need to adaptive to different tissues, have to use vision, small devices.
Industrial solution requirements: environment can be controlled, robust, high speed, quality control.

2 State of the art

In this section, we give an overview of the existing intelligent sewing technologies and provide an insight and review on their applications in medical sewing and industrial sewing.

2.1 Medical sewing

2.1.1 Mechanical design and clinical requirements

(clinical requirements: Celia)

Intracorporeal suturing is probably one of the most difficult tasks, which can complicate, prolong or preclude minimally invasive surgical procedures. Most suturing tasks can be divided into two procedures: tissue piercing and knot tying. In the tissue piercing procedure, most importantly, the surgeon needs to guarantee a minimal damage to the tissue when driving the needle tip to the exit point, which requires a robust needle driving mechanism to drive the needle follow a critical path. On the other hand, with conventional laparoscopic tool, the knot tying procedure is commonly conducted by winding the suture around a grasper and then use the same grasper to pick the end of the suture through the loop. With limited intracorporeal space and constrained degree of freedom, the knot tying prcedure is also very challenging. Various technologies have been develop for the purpose of providing robust needle driving during tissue piercing procedure. A commercial available laparoscopic suturing device is the SILS^{TM} Stitch instrument (Covidien), which performs stitching by passing a straight needle between two grasper jaws. Endo360 suture tool (EndoEvolution, LLC) is another device for the same purpose. It features a curved suture needle driven along a circular path. Suturing assistance devices also developed for other surgical procedures, such as OverStitch (Apollo Endosurgery Inc, Austin, Tex) for endoscopic surgical closure, SafeStitch Medical Gastroplasty System (Tu et al., 2012) for conducting suturing in gastroesophageal junction, Capio SLIM Suture Capturing Device (Boston Scientific Ltd) for providing consistent suture placement in pelvic floor locations where are difficulty to access.

2.1.2 Sensing and feedback

In the automation of surgical sewing, i.e. suture, sensing of the environment is essential. As the task context, i.e. the environment of suture, various case by case, the suture motion can not be hard coded and has to be adaptive to the current situation. The main sources of sensing in a surgical task are vision and haptic.

Vision guilded suturing has been a popular topic since those prioneer works () in automatic suturing. A large amount of works focus on locating the needle piercing positions provided by human and moving the needle to the correct spots. (Staub et al., 2010) use a single camera to servo the needle to the marked piercing positions. Four markers are sticked to the surface of suture and calibrated to estimate the depth of this surface. After locating the 3D piercing positions, a path is planned for the robot to execute the suturing task. To increase the accuracy of the needle piercing, 3D stereo camera is oftenly used. (Iyer et al., 2013) use a 3D camera to track the needle position globally, while use a 2D camera to locally adjust the needle pose for piercing. In this work the error of positioning is controled within 1mm.

2.1.3 Motion planning and control

Even with the help of robotic surgical systems, suturing is a challenging and time consuming task during Minimally Invasive Surgery. Automating the suturing task may reduce both the time and difficulty of completing a suture. Commonly, surgical suturing is conduct bimanually via a circular needle. In terms of the suturing depth, operation space and types of tissue, there are various needles and needle holders to be selected. Surgical suturing involves both tissue piecing and knot tying. It can be described as following steps: 1 Grasp the needle, move and orient it such that the tip is aligned with the entry point. 2 Pierce the tissue so that the needle enters the tissue, and continuously push the needle until it gets out from the exit point. 3 Grasp the needle tip with the other needle holder and pull the needle out. 4 Create a suture loop to tie a knot with both hand and secure the knot under proper tension. There are many general principles that surgeons use to complete a suturing stitch. First, during the piecing process, the needle tip is better to be moved tangentially to its curve direction so that no unnecessary stress is applied on the tissue. Second, the re-grippable length of the needle during the suture must be adequate for re-grasp. In addition, for the knot-tying process, complex movements between needle driver with needle driver and needle driver with thread are required. Due to the geometrical constraints, to automate the surgical suturing process, movement planning have been investigated on both stitching and knot-tying.

Nageotte et al. (2005, 2009) present a method for planning the needle path for tissue piecing. They have shown that with the knowledge of the position and orientation of the needle in the needle holder, it could be possible to predict the optimal entry points of the needle, the piercing angles and the deformations of the tissues. Besides automating surgical suturing, the method can be also applied to suturing training with the path being shown to the surgeon by augmented reality. Another needle path planning scheme with the purpose of minimizing tissue needle interaction force has been proposed by Jackson and Cavusoglu (2013). The tissue piecing procedure is divided into a series of individual steps. Based on different quantitative measurement, two distinctive trajectories for the semi-circle needle are planned and compared in their scheme.

In another work presented (Khabbaz and Patriciu, 2011), tissue deformation is modelled in order to predicting the desired needle exit point. Ding and Simaan (2014) regards the choice of piercing path along the circular needle body is too conservative and the minimal constraint suturing is proposed. In addition, in their work, a shared-control teleoperation framework whereby the surgeon controls the needle insertion speed and the robot controls the needle orientation was used. On the other hand, with conventional laparoscopic tool, the knot tying procedure is commonly conducted by winding the suture around a grasper and then use the same grasper to pick the end of the suture through the loop. With limited intracorporeal space and constrained degree of freedom, the knot tying procedure is also very challenging. Nagy et al. (2004) were the first to tie a suture knot autonomously using general purpose laparoscopic instruments. Chow and Newman (2013) have planned two path for the surgical instrument to tie Surgeons knot under the laparoscopic constraints.

2.1.4 Learning

Mayer et al. (2008) learn the winding part of knot tying from human's demonstration by using recurrent neural networks (RNNs). Their EndoPAR system is a four-ceilling mounted robots system, with three holding laparoscopic gripper instruments and one holding an endoscopic stereo camera. Two of the gripper instruments are fixed and the motion of the third one is generated by the learnt RNNs. As a knot typing trajactory is time dependent, the Long Short-Term Memory method is used to correctly judge the current status of the task. Padoy and Hager (2011) use the Hidden Mackov Model (HMM) to encode human demonstated suturing trajectories and automated the bimanual suturing procedure with a curved needle. During the suturing task, human make a decision of where to sew and the robot will execute the stitch. Van Den Berg et al. (2010) smooth human demonstrated trajectories of a knot tying motion and use interative learning control to improve the execution accuracy. The speed of knot tying is gradually speeded up to 7 to 10 times than the demonstations by updating the control parameters iteratively. Thses studies presumn the task contexts are the same for the demonstation and task execution. Padoy and Hager (2011) do a case study on transfering the demonstrated trajecory to different task contexts, i.e. different geometries of the suturing surface. They select critical points from the suturing surface of demonstration and calculate the transfromation between these points and their corresponding points testing suturing surface.The demonstrated trajectory is then transfered to the new task context by the same transformation. This method shows good successful rate (87%) in small deformated surface (rotation and bend). To effectively learn a complex, multi-step surgical motion, motion segmentation techniques are used to segment the task demonstrations (Lin et al., 2006). Krishnan et al. (2015) segment the motion sequence by using vectors that composed by the current state and the next state of the task as features. These features are clustered by the Dirichlet Process Mixture Model. The segmentation points, refered as the "milestones", are identified by two consective features that do not belong to the same cluster.

2.2 Industrial sewing

2.2.1 Integrated sewing systems

Fabric sewing is common yet critical to many industrial manufacturing processes. However, this process is still labour intensive and less automated compared with others manufacturing processes, such as arc welding, car assembling, ect. The main reason that impedes the automation of sewing industry lies in the difficulty to handle limp material. State-of-the art robotic sewing process makes articulated robots cooperate with computerized sewing machine for controlling sewing direction and maternal tension. Feedback control with force sensors reduces the fabric buckling and vision system tracks patterns on the fabric. An earlier work of robotic sewing is the FIGARO system (Gershon and Porat, 1986, 1988), which contains an articulated robot with two finger end-effector, a sewing machine, vision system on the sewing machine and a force sensor mounted on one the two fingers. With the aid of both visual and force information, two closed-loop control system are maintained: the first one makes the robot keep the tension of the fabric being fed into the sewing machine; the second visual servoing control loop maintain the sewing is moving along a pre-programed trajectory. In order to execute the task in a similar manner as does the human operator, bimanual robotic sewing was proposed by Kudo et al. (2000) to maintain fabric tension, which used a hybrid position /force control strategy. Similar bimanual sewing system was also developed by Schrimpf and Wetterwald (2012); Schrimpf et al. (2014) for joining parts with different shapes. The controlling strategy is based on switching between force control and displacement control using a leader/follower coordination scheme. Pattern sewing requires a precise control of the fabric feeding direction. The most common pattern is a straight line. To guide the human operator, state-of-the-art sewing machines with innovative laser guide can project a perfect straight laser beam onto the fabric. In robotic sewing process, the visual guidance is commonly based on using camera system and visual servoing algorithm. Besides using camera, other types of optical sensor system have been proposed. A 1-D optical sensor array, which can measure the amount of light in each pixel, was used for controlling the edge distance (Schrimpf and Wetterwald, 2012; Schrimpf et al., 2014). Artificial features are created to help increase sewing accuracy. In another work, a laser beam was projected onto the seam to be sewed (Biegelbauer et al., 2007). By an interpretation of the geometrical relation between the sewing seam and laser beam in the camera image, an accurate sewing trajectory tracking can be achieved. Conventional sewing technique are restricted to work on a flat plane with limited size, because the commonly used lock stitch or chain stitch need access to both sides of the material, which requires a sewing machine with bottom or looper mechanism working on the bottom side. For sewing on 3-D structure with larger scale, the robot manipulators were introduced to hold the customized sewing machine. To solve the great difficulties in accessing from both sides, various single sided sewing techniques are developed (Brandt et al., 2002). There techniques include ITA multi-thread chain stitch sewing machine using two needles, ALTIN chain stitch sewing machine using a needle and a hook and KSL blind stitch with a curved needle.

2.2.2 Vision and visual servoing

Vision guidance Staub et al. (2010); Iyer et al. (2013)
Fabric detection In industrial sewing, vision is mainly used to handle the unpredictable behavior of the soft materials. This includes detection of fabric location and deformation, stitch counting, following preplanned seam path. Many sewing machine companies have their own patents, which use well extablished computer vision techniques such as tracking and segmentation to monitor and control the stitch quality (**??**). For fabric location, the most commonly used features are fabric edges and vertexes. The motion of vertexes and edges are tracked and hence determine the robot end effector motion (Torgerson and Paul, 1988; Gershon and Porat, 1988; Richtsfeld et al., 2010). In many tasks of handling deformable materials, a single source of the sensing is not adequate. In those tasks, multisensor system is deployed to query a better sensing effect. Koch et al. (2013) present a system with vision, force sensor and accelerometer. The vision is used to steers the robot effector to follow a contour, the force feedback to control the contack force between the robot and the environment, while the accelerometer to compensate the extra force sensor reading due to acceleration. The vision and force feedback are associated to compensate the deformation caused by robot contacting the environment.

2.2.3 Control

Fabric (deformable objects) manipulation and tension control Carvalho et al. (2010); Schrimpf and Wetterwald (2012); Schrimpf et al. (2014)
Quality control

3 Future research challenges and opportunities

(Su-lin and Beny?)
Using medical sewing techniques to manufacture personalized stent graft manufacturing Santos et al. (2012); Duffy et al. (2013)

4 Conclusion

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Table 1 Properties of intellegent sewing systems

Work	Automated Tasks	Robot	Sensing			DoF	Stitch Types
			Vision	Force/Torque	Others		
(Van Den Berg et al., 2010)		Berkeley Surgical Robots					
(Schulman et al., 2013)		Raven II + Phantom OMNIs, PR2					
(Koch et al., 2013)	Contour Following	KUKA KR60-2	3D camera	Force Torque sensor	Accelerometer		

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