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Video Assisting System for Garment Manufacturing Technological Flow

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Abstract
Although numerous video-inspecting systems have beenimplemented in different manufacturing domains, in the textile industry there is no video assisting/inspecting of assembling operations in the textile/clothes production flow available on the market. There are some particularities of textile and clothes manufacturing units, severely restricting the customisation of existing video assisting systems to the garment industry. Among these, the most important are the irregularity of lighting caused by the partial obstruction of the optic path (flocks and fluffs interposing between the light source – textile detail – video cam) as well as the presence of fabric undulations which can modify the visible shape of the detail to be identified. In order to overcome these limitations, a novel pattern matching algorithm was developed, named the Learn and Match Mini-Pattern. The working principle of this new algorithm will presume the decimation of a pattern in several partial mini patterns.

Key words: *video inspection, pattern matching, testing, automation.*

Introduction

Worldwide, the textile industry and other industrial sectors are still in recession. To cope with the crisis and to develop a framework for a more dynamic and competitive global market, textile companies have to meet market requirements via the ‘fast fashion reactive’ concept, meaning that they should be able to manufacture small quantities of high difficulty and high added value products. Moreover the products’ quality certification represents a high priority. Accordingly companies have to demonstrate the presence of a quality assurance system within their processes.

Cutting machines, pattern layouts and other functions are computer-assisted and, in many cases, patterns can be created from designs which can then be electronically transferred to automatic machines to cut. These innovations are mainly related to the so-called pre-assembly phase of production, where technological developments have been more prominent than at the assembly stage. However modern, the assembly (sewing) stage of the clothing sector is still labor-intensive and it is still the stage that is most likely to increase garment cost. The individual sewing tasks are organised in a systematic fashion and specialized sewing machines have been developed for the individual tasks. A worker receives a bundle of unfinished garments (pieces), performs her single task and passes along the production line.

Since labour costs are a high proportion of the total cost the competitiveness of textile and clothes manufacturers is dependant on adopting new innovative solutions to reduce the sewing operation duration and to improve the quality of their products.

Currently in the textile industry, the concerns of different research groups in the domain of image processing applications are directed towards systems that pass the fabric inspection at the fabric producers (woven, unwoven and knitted) or in clothing factories, prior to the cutting process [1 - 13]. Also systems for monitoring the manufacturing process of textile fibres and measuring their characteristics were developed as well [14 - 19]. A recent concern is represented by the 3D simulation of the human body’s dimensional characteristics, with the aim of developing personalised patterns for clothing fabrication [20, 21].

Studies regarding the development of video assisting systems for the final stages of the clothes manufacturing process are limited. A basic approach can be found in developing a system for measuring the dimensions of final warp products with the scope of establishing the stretching degree of the fabric during the washing process [22]. The most recent researches were undertaken in order to determine the seam’s quality (stretching, gaps etc.) [23] and methods for the image processing of final product dimensions [24].

In this context, this paper presents a video-processing system (VidAssist) with the role of the dimensional monitoring of the sewing operation. The system will assist workers in establishing the sewing position of different textile pieces in the interphase process of production and also for inspecting assembly accuracy.

Description of VidAssist system

Although numerous video-inspecting systems have been implemented in different manufacturing sectors such as the production of electronic components and printed circuits [25 - 29], the production of aluminium [30], steel [31] and glass [32], the automotive industry [33 - 35], agricultural industry [36, 37], and chemical and medicine industry [38 - 43], in textiles there is no other video assisting/inspecting of the assembly operations system available in the textile/clothing sector.

There are some particularities of textile and clothes manufacturing units severely restricting the customisation of existing video assisting systems to the garments industry. Among these, the most important are the irregularity of lighting caused by the partial obstruction of the optic path (flocks and fluffs interposing between the light source – textile detail – video camera) as well as the presence of fabric undulations which can modify the visible shape of the detail to be identified.

In order to overcome these drawbacks, a novel pattern matching algorithm is developed in this paper, named the Learn and Match Mini-Pattern.

The VidAssist algorithm will identify, from the image flow acquired in real time, the interest elements of a technological phase based on their patterns previously memorized. Once the interest elements are identified, specific functions for the dimensional characterisation of these elements or for distance evaluation between the elements and several imposed landmarks are to be applied.

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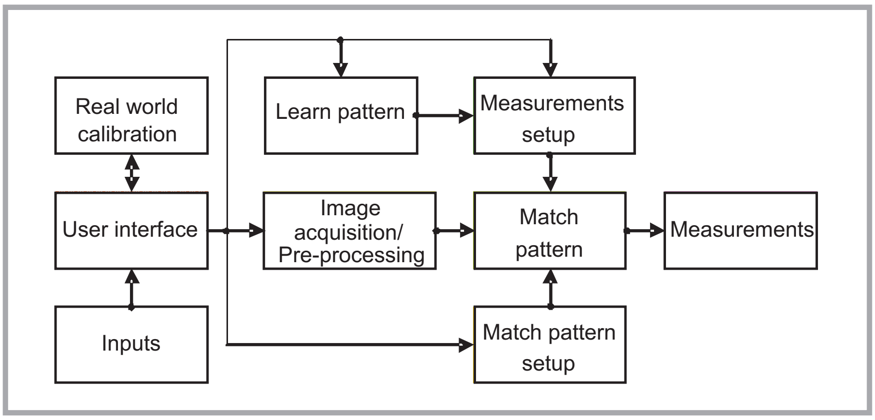

Figure 1. *VidAssist software bloc diagram.*

A block diagram of the assisting algorithm for the textile manufacturing process, depicted in ***Figure 1***, is composed from the following routines: Real world calibration, User interface, Inputs, Image acquisition/Pre-processing, Learn pattern, Measurements setup, Match pattern, Match pattern setup and Measurements.

The User Interface is developed in a friendly manner which allows an intuitive utilisation, not requiring programming skills of the users. The great diversity of garments, the variety of requirements regarding the quality threshold, and the diversity of the process levels (inter-phase, final) impose a high degree of adaptability on the video inspecting/assisting system in introducing the inputs. The inputs refer to the reference dimensions of the elements investigated, as well as to the accepted tolerances. The pattern image of the interest elements is loaded by the production sample.

After installing the video acquisition camera in the technological process, Real world calibration will be run, consisting in locating/mounting on the work bench a grid of known dimensions. For the image acquired the number of pixels of the grid's side will be converted into length units (millimeters). The calibration will be executed each time the video camera is moved to another part of the technological process.

Prior to the start of the assisting/inspecting procedure, it is necessary to load the interest elements as patterns (Learn pattern). Thus from the production sample, a reference image will be loaded, and the user will graphically establish the pattern (a pocket, a set of buttonholes, a group of stitches, a detail area, etc.). This operation is executed once for each model.

After the image containing the pattern is loaded, graphic tools can be used to specify which element is to be measured/tested (Measurements setup). This element may belong to the pattern or may be located outside it. Within the same procedure, the reference coordinates for distance measurements are automatically defined.

The Match pattern setup procedure establishes the manner in which the pattern is matched to a new image (matching through shade or shape, contrast threshold, matching score a.s.o).

The pattern of the interest element, already loaded from the production sample in the Learn pattern routine, will be identified in the online images acquired during the technological process. The Match pattern routine will allow its identification regardless of the interest element's rotation during the acquisition process. The pre-processing routine is aimed at eliminating the overlapped noise from the images processed. Adaptive filtrations were used to remove the false defects.

In the manufacturing process, image processing of different textile details can be affected by the partial obstruction of the optic path (light source – textile detail – video camera). If the disrupting element is obstructing the light source – textile detail path, then we are facing a strong

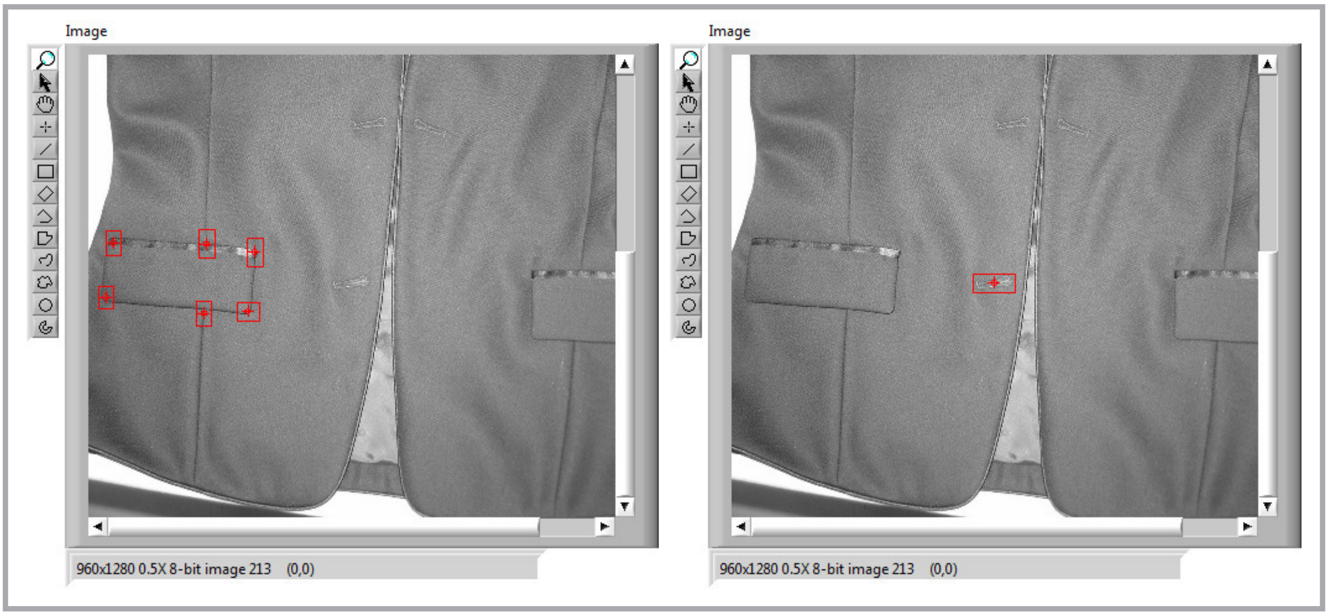

Figure 2. *Patterns for the two references investigated.*

irregular lighting gradient, and if the disrupting element is interposed between the textile detail and video camera, we are facing an incomplete visualisation of the textile detail. Another disruptive factor specific to textile fabrics is the presence of fabric undulations which can modify the visible shape of the detail to be identified.

The system's implementation allows the removal of the disruptive factors of the video processing above with the help of the Mini-Pattern.

Taking into account the fact that the assisting algorithm of the textile manufacturing process is based on the Pattern Recognition cycle, it is obvious that the influence of disruptive factors will be found in applying the Learn and Match Pattern routines. In this situation, the Pattern Recognition routine was developed based on new functions named the Learn and Match Mini-Pattern. The working principle of this new algorithm presumes the decimation of a pattern into several partial mini patterns. Pattern identification is made on the basis of Mini Patterns which meet the match scorer in two steps: Match Mini Pattern (calculation of the match scoring of the Mini Patterns and selection of those which exceed the matching threshold) and pattern reconstruction (pattern reconstruction based on the Mini-Patterns exceeding the matching threshold). The lower matching thresholds as compared with the threshold imposed are caused by the Mini-patterns affected by the disruptive factors, and will be discarded.

Pattern recognition cycle of VidAssist system

The Pattern recognition cycle is performed in two stages: The first stage, offline, consists in loading the patterns and establishing the element to be measured. The second stage, online, consists in identifying the loaded patterns in the technological process and applying the measurement functions previously established. Next the two stages are presented

First stage, offline

The patterns for the two interest elements (the pocket flap and buttonhole) are loaded from the production sample (***Figure 2***). The pocket flap requires a loading of the pattern in the form of a Mini-Pattern because its surface is larger and during the manufacturing/assembling it may be subject to disturbing factors. Since the flap assembly is inter-phase performed, two investigation stages are executed: one for inter-phase assistance and one for final quality control. In the inter-phase stage the positioning of the flap is continuously checked according to the front bodice seam so as to achieve the assistance of the assembly operation. Since the buttonhole has small dimensions and is built on a stable structure, classic pattern loading will be done.

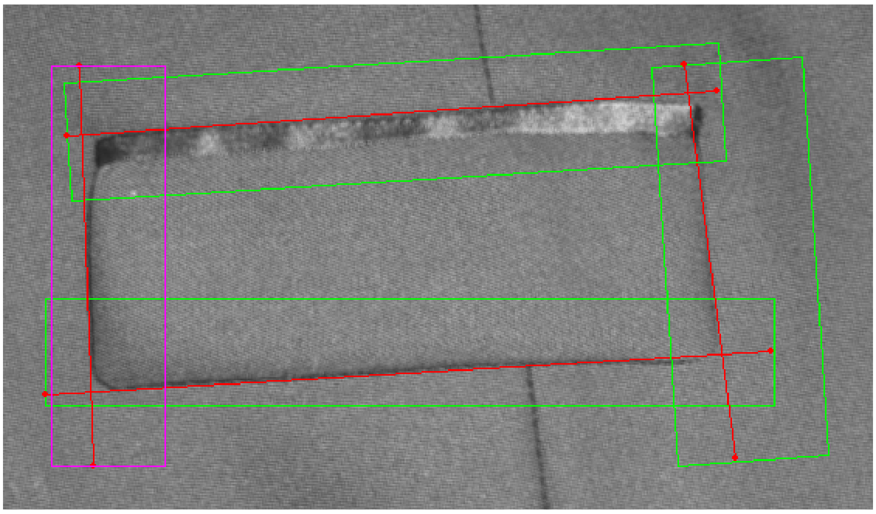

Figure 3. *Pattern reconstruction of the pocket flap.*

Based on the Mini-Patterns loaded for the pocket flap, the unitary pattern reconstruction is performed using edge detection functions applied in areas of interest dictated by the Mini-Patterns locations (***Figure 3***).

The pattern reconstructed represents the coordinate system to which the dimensional measurements of the elements monitored will be specified. For the pocket flap positioning the element monitored is the front bodice seam. A dimensional measurement will be made to determine the distance from this seam to the left side of the right pocket (as worn) (***Figure 4,*** see page 138).

The measurement algorithm involves the extraction of a colour plane from the colour image acquired, performing local filtering in order to reduce the fabric striations, setting the region of interest (ROI) positioning (according to the reconstructed pattern) in order to search for pattern edges, making the intersections and calculating the distance between the points of intersection.

Second stage, online

The online stage is inter-phase performed to assist the assembly of the pocket flap and in the end to inspect the position of the flap and buttonhole. During the inter-phase technological process the pattern loaded in first stage is identified (***Figure 5,*** see page 138), which used as a reference system for the application of the ROI where the edges are identified, and the intersections are established with the same algorithm presented in the first stage.

Even if the points between which the measurement is performed are identified during the first stage as Mini-Patterns, these are not used in the second stage. Instead an independent method based on edge detection is used because during the investigation from the second stage, some Mini-Patterns may not be identified due to the existence of disturbing factors.

Although the pocket flap position, according to the front detail, is inter-phase assisted, at the end, the flap position, according to the ready garment, may not be correct. During the assembly process of the front detail (which contains the pocket flap) with other tailored details (facing, lining), the flap position, according to the front edge and hem edge, may be diverted when the assembly reserve is incorrect. In this situation it is necessary to perform an inspection of the ready garment.

Inspection of the ready garment is made by identifying the flap and pocket pattern, followed by edge identification. The perpendicular between the flap edge and front edge is determined and its dimension calculated, or for the buttonhole the distance between the centre of the buttonhole pattern and the intersection between the hem edge, and the perpendicular which goes through the centre of the pattern is calculated (***Figure 6***).

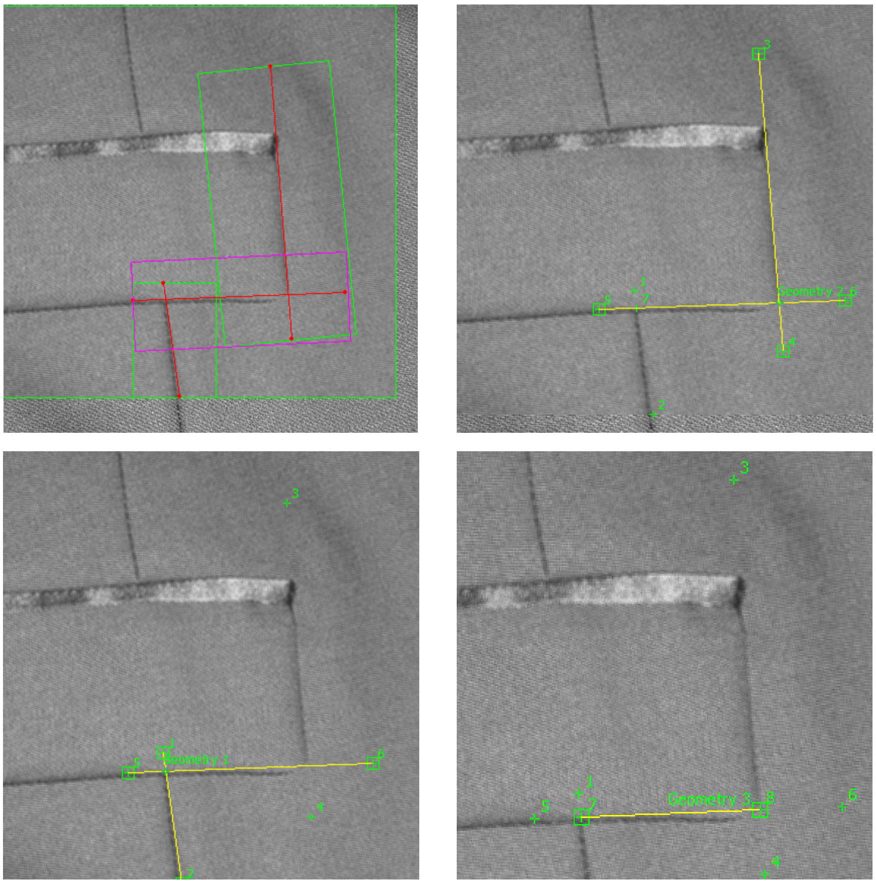

Figure 4. *Distance measurement between the front bodice seam and left side of the right pocket.*

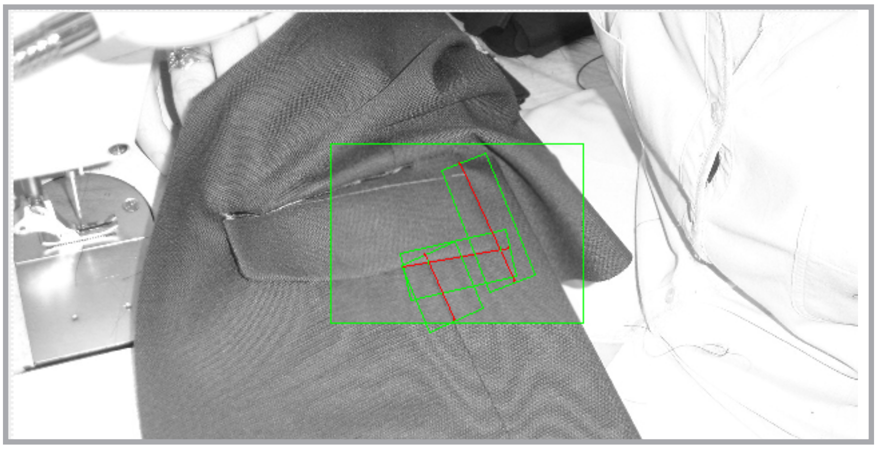

Figure 5. *Inter-phase pocket flap assistance.*

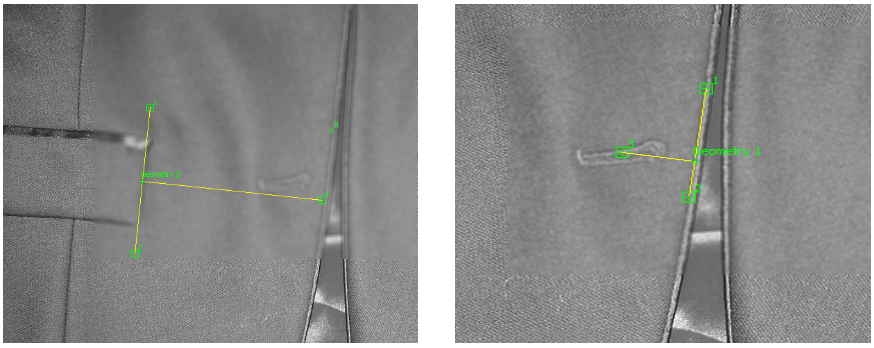

Figure 6. *Ready garment inspection (pocket flap and buttonhole).*

Experimental results

Experimental tests were done at the Cristian ABC Company, Iaşi, Romania, on a test lot of 1456 jackets with a size group of 36 - 56 in production for a client. In accordance with the technical sheet of quality control, the following interest elements were chosen to assist/measure in the manufacturing process: pocket flap sewing with inter-phase assistance and final quality control and buttonhole positioning with final quality control.

Assisting/inspecting the pocket flap's positioning was done by tracking the distance between the front bodice seam and pocket's edge. Inspection of the buttonhole's positioning was done by tracking the distance between the centre of the buttonhole and front edge.

For sizes 36 - 42 (first half of garments) the inter-phase assisting (IFA) of the pocket flap's positioning was not performed, and sizes 44 - 56 (last half of garments) were assisted by VidAssist in positioning. The buttonhole's positioning, as a final operation of the technological flow, was inspected during the quality control of the ready garments. Both for the pocket flap and buttonhole, a comparison was made between the inspections made by the human operator and the VidAssist system. The inspection performed by the human operator was made piece by piece, not statistically. Defects detected during the inspection stage were rated as minor if they exceed the dimensional tolerance by less than 20% and major if they exceed it by more than 20%. Experimental results are presented in ***Table 1***.

In accordance with the measurement chart, the distances investigated have the following values:

- inter-phase assisting, the distance between the front bodice seam and flap's horizontal edge – 4.1 cm, with an allowed tolerance of 0.2 cm;
- final inspection, distance between the pocket flap edge and front edge - 11.4 cm, with an allowed tolerance of 0.2 cm;

- final inspection, distance between the buttonhole's centre and front edge - 2.9 cm, with an allowed tolerance of 0.2 cm.

As can be seen from the experimental results there are no significant differences between the two methods in terms of identifying major defects within the final quality control. Both the human operator and VidAssist detected 4 major defects for the pocket flap and 3 and 4 major defects, respectively, for the buttonhole. An increase in the rate of minor defect detection can be observed when the VidAssist system is used compared with the case for a human operator . The human operator detected 20 pocket flap and 36 buttonhole defects while VidAssist detected 26 and 63, respectively.

Major differences occur in the sense of a significant reduction in the rate of defect occurrence when the VidAssist system is used in the inter-phase stage of the manufacturing process. Thus, using VidAssist final inspection, a reduction in major defects from 4 to zero can be observed, and a reduction in minor defects from 22 to 4, compared to when inter-phase assisting is used. These results are depicted in ***Table 2***.

Table 1. *Experimental results for a test lot of 1456 jackets.*

Size	**Ratio**	**No. of jackets**	**No. of defects – pocket flap**				**No. of defects – buttonhole**				**Obs**
			Human operator		**VidAssist**		**Human operator**		**VidAssist**		
			minor	**major**	**minor**	**major**	**minor**	**major**	**minor**	**major**	
36	3	156	2	0	2	0	3	1	5	1	**-**
38	3	156	5	2	7	2	4	0	8	0	**-**
40	4	208	6	1	6	1	5	1	9	1	**-**
42	4	208	5	1	7	1	4	0	5	1	**-**
44	4	208	0	0	0	0	6	0	6	0	**IFA**
46	3	156	1	0	1	0	5	1	7	1	**IFA**
48	2	104	0	0	1	0	0	0	4	0	**IFA**
50	2	104	0	0	1	0	4	0	5	0	**IFA**
52	1	52	0	0	0	0	1	0	5	0	**IFA**
54	1	52	0	0	0	0	2	0	6	0	**IFA**
56	1	52	1	0	1	0	2	0	3	0	**IFA**
T	**28**	**1456**	**20**	**4**	**26**	**4**	**36**	**3**	**63**	**4**	

Table 2. *Results of VidAssist final inspection.*

VidAssist final inspection	**Minor**	**Major**
Without inter-phase assisting	**22**	**4**
With inter-phase assisting	**4**	**0**

Conclusions

VidAssist is suitable especially for uniforms and other large orders. Significant diminishing of the defect occurrence rate is obtained if the inter-phase production flow system is used. Preliminary estimations we made about the efficiency of the video assisting system proposed for textile manufacturers revealed an up to 40% decrease in the sewing process duration. In terms of garment cost it means a 10% cut.

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