Chair for Computer Science 10 (Media Computing and Human-Computer Interaction)

RWTH AACHEN UNIVERSITY

How is your sewing?

Using Image Recognition for Sewing Skill Assessment

Bachelor's Thesis
submitted to the
Media Computing Group
Prof. Dr. Jan Borchers
Computer Science Department
RWTH Aachen University

by
Judith Ernstberger

Thesis advisor:
Prof. Dr. Jan Borchers

Second examiner:
Prof. Dr.-Ing. Ulrik Schroeder

Registration date: 09.08.2023
Submission date: 11.12.2023

Zentrales Prüfungsamt/Central Examination Office

RWTH AACHEN UNIVERSITY

Eidesstattliche Versicherung
Statutory Declaration in Lieu of an Oath

___________________________ ___________________________

Name, Vorname/Last Name, First Name

Matrikelnummer (freiwillige Angabe)
Matriculation No. (optional)

Ich versichere hiermit an Eides Statt, dass ich die vorliegende Arbeit/Bachelorarbeit/ Masterarbeit* mit dem Titel

I hereby declare in lieu of an oath that I have completed the present paper/Bachelor thesis/Master thesis* entitled

____

____

____

selbstständig und ohne unzulässige fremde Hilfe (insbes. akademisches Ghostwriting) erbracht habe. Ich habe keine anderen als die angegebenen Quellen und Hilfsmittel benutzt. Für den Fall, dass die Arbeit zusätzlich auf einem Datenträger eingereicht wird, erkläre ich, dass die schriftliche und die elektronische Form vollständig übereinstimmen. Die Arbeit hat in gleicher oder ähnlicher Form noch keiner Prüfungsbehörde vorgelegen.

independently and without illegitimate assistance from third parties (such as academic ghostwriters). I have used no other than the specified sources and aids. In case that the thesis is additionally submitted in an electronic format, I declare that the written and electronic versions are fully identical. The thesis has not been submitted to any examination body in this, or similar, form.

___________________________ ___________________________

Ort, Datum/City, Date

Unterschrift/Signature

*Nichtzutreffendes bitte streichen

*Please delete as appropriate

Belehrung:
Official Notification:

§ 156 StGB: Falsche Versicherung an Eides Statt

Wer vor einer zur Abnahme einer Versicherung an Eides Statt zuständigen Behörde eine solche Versicherung falsch abgibt oder unter Berufung auf eine solche Versicherung falsch aussagt, wird mit Freiheitsstrafe bis zu drei Jahren oder mit Geldstrafe bestraft.

Para. 156 StGB (German Criminal Code): False Statutory Declarations

Whoever before a public authority competent to administer statutory declarations falsely makes such a declaration or falsely testifies while referring to such a declaration shall be liable to imprisonment not exceeding three years or a fine.

§ 161 StGB: Fahrlässiger Falscheid; fahrlässige falsche Versicherung an Eides Statt

(1) Wenn eine der in den §§ 154 bis 156 bezeichneten Handlungen aus Fahrlässigkeit begangen worden ist, so tritt Freiheitsstrafe bis zu einem Jahr oder Geldstrafe ein.

(2) Straflosigkeit tritt ein, wenn der Täter die falsche Angabe rechtzeitig berichtigt. Die Vorschriften des § 158 Abs. 2 und 3 gelten entsprechend.

Para. 161 StGB (German Criminal Code): False Statutory Declarations Due to Negligence

(1) If a person commits one of the offences listed in sections 154 through 156 negligently the penalty shall be imprisonment not exceeding one year or a fine.

(2) The offender shall be exempt from liability if he or she corrects their false testimony in time. The provisions of section 158 (2) and (3) shall apply accordingly.

Die vorstehende Belehrung habe ich zur Kenntnis genommen:

I have read and understood the above official notification:

___________________________ ___________________________

Ort, Datum/City, Date

Unterschrift/Signature

Contents

List of Figures

List of Tables

Abstract

A growing community is working on privately-driven projects in all kinds of fields in handcrafting Mota [2011]. Consequently, there are numerous resources available, online and offline, that inspire, help and guide people in the maker community. We identify a need for automated tools and aid in personal fabrication to assist the process of finding suitable tutorials and offer objective skill assessments.

This bachelor thesis focuses on sewing, a craftsmanship consisting of multiple theoretical and practical skills. We find ways of automatically assessing individual users' practical sewing skills by proposing a ready-to-use application. The objectiveness of our implementation helps sewers gain insight into their current level of expertise and provides graphical feedback and analysis on their resulting task.

Our work continues the findings in Rahm [2022], which amongst other things explored factors indicating the quality of a sewed product. Rahm proposed a theoretical prototype of an automated skill evaluation that integrates a practical sewing task. We realize part of the assessment which focuses on evaluating a user's ability to sew along a given line with a consistent distance, mimicking the seam allowance in practice. By using color detection to determine seams and lines we are able to apply a coarse registration algorithm to match both components onto each other. This helps us in analyzing how parallel the stitching was placed next to the given line. Based on the resulting overlapped lines our application returns objective feedback variables that refer to the parallelism kept while sewing.

The proposed approach in this thesis contributes to the development of automated tools for personal fabrication and constitutes a way of assessing practical handcrafting skills directly.

Überblick

Durch die wachsende Gemeinschaft von Hobbyhandwerkern verschiedenster Fachbereiche lassen sich zahlreiche Inspirationen und Anleitungen, sowohl online als auch offline, finden Mota [2011]. Hierbei soll sowohl die Suche nach geeigneten Anleitungen als auch der Bewertung der relevanten Fähigkeiten jenes Bereiches durch automatisierte Systeme erleichter werden.

In dieser Bachelorarbeit wird sich dem Handwerk des Nähens gewidmet, welches theoretisches als auch praktisches Können umfasst. Die entwickelte Anwendung zur automatischen Bewertung der praktischen Nähfähigkeiten bietet für Näher eine objektive Einschätzung ihrer aktuellen Fachkompetenz.

Es wird an die Ergebnisse in Rahm [2022], in der unter anderem Wege untersucht wurden, die Qualität eines genähten Produkts zu bewerten, angeknüpft. Rahm konzipierte hierbei einen Prototyp eines automatisierten Systems zur Bewertung von Nähfähigkeiten, welche auch eine praktische Aufgabe beinhaltet. In dieser Arbeit wird der Teil jenes Prototyps umgesetzt, welcher das parallele Nähen evaluiert. Der Nahtzugabe entsprechend, sollen Nutzer mit konstantem Abstand entlang einer vorgegeben Linie nähen. Mithilfe von Techniken der Computer Vision werden die fotografierten Nähte und gedruckten Linien bestimmt. Prinzipien der groben Registrierung werden zudem angewendet um beide Komponenten übereinander zu legen und somit die Naht mit der vorgegeben Linie zu vergleichen. Dadurch kann die Parallelität der genähten Linie rechnergestützt bewertet werden. Basierend auf den resultierenden überlappenden Linien gibt unsere Anwendung ein objektives Feedback in Form von berechneten Werten zurück, welche sich auf die beibehaltene Parallelität beziehen.

Der in dieser Arbeit vorgeschlagene Ansatz trägt zur Entwicklung automatisierter Hilfsmittel für Hobbyarbeiten bei und stellt eine Möglichkeit dar, praktische Handwerksfähigkeiten direkt zu bewerten.

Acknowledgements

First, I would like to thank Prof. Dr. Jan Borchers and Prof. Dr.-Ing. Ulrik Schroeder for examining this thesis.

I would also like to thank my advisor Marcel Lahaye for his encouraging mentoring and insightful guidance throughout this journey.

Conventions

Throughout this thesis we use the following conventions.

Source code and implementation symbols are written in typewriter-style text.

`myClass`

The whole thesis is written in American English. We use third person plural to refer to an unidentified third person.

Chapter 1

Introduction

Most DIY tutorials do not offer skill-oriented content despite its relevance for handcrafting guides

Finding handcrafting tutorials that interest you as well as suit your current skills in a field within today's information offer can be time-consuming and frustrating. Often, in each handcraft, there are multiple individual skills one can acquire and be judged by. Besides several theoretical knowledge that can be gained about tools, workflow, or optimal functionality, there is always a broad field of practical skills to achieve. Although nowadays there are numerous different platforms and applications offered to learn and teach about a wide range of personal fabrication, few specify in respective skills recommended for carrying out their tutorial. This may result in avoidable nuisance due to tasks of high difficulty or simplicity. We therefore look for an automated skill assessment to gain insights on a user's level of expertise to return feedback on the tested proficiency. Such a solution not only helps us in recommending suitable tutorials for each user but additionally benefits the user in terms of objective analysis and rating of their completed task.

Growing community of crafters search for resources online

The ongoing rise of personal fabrication offers opportunities for exchange on a large scale Mota [2011]. Platforms and websites such as YouTube[1], Instructables[2] or TikTok[3] either aim for or naturally offer instructions on DIY (Do-it-yourself) projects in numerous crafting fields.

[1]https://www.youtube.com
[2]https://www.instructables.com
[3]https://www.tiktok.com

Relevance of user-centered innovation

Whereas service and products developed by the manufacturer focus on the capitalization of those, user-centered innovation concentrate on their usage von Hippel [2005]. This leads to different interests lying in the foreground. The latter enables interest-oriented innovation allowing rapid changes without governmental regulations. Additionally, a widespread exchange of ideas allows for quick adaption and modification of existing products, solving user-relevant issues. Overall, within fabrication as well as the research community user-centered innovation plays an important role, We conclude that there is a need for toolkits in the form of hardware and software to help people innovate and spread their ideas. Moreover, by adding to DIY tutorials we support and give aid to the community of handcrafting, enabling further innovation.

Continuation of Rahm's work on developing an automated sewing skill assessment

The handcraft of sewing comprises expertise in multiple distinctive areas. In her Master's thesis, Rahm explored the different skills that are relevant for this handcraft by interviewing professionals in that area Rahm [2022]. After gaining insights into which skills can be assessed and what traits of a sewed product can help identify to testify a person's sewing skills, she designed a prototype to automatically evaluate relevant knowledge. We continue her work by realizing part of said prototype that focuses on testing users' practical sewing skills.

Multiple aspects to determine sewers' expertise

When asked about which factors sewing experts examine on a sewer as well as on a sewed product to classify the sewing skills of the respective sewer, the experts referred to multiple properties. For assessing the sewing skills of a person, they mentioned aspects observable during the process of sewing, such as the handling of the sewing machine or the speed, as well as logical skills and motivation. Further, the quality assessment of a sewed product includes the examination of the seams and which materials were used. Figure 1.1 shows an overview of their answers on this issue, in which seam allowance is mentioned as one of them.

Evaluating users' ability to keep a consistent seam allowance

For practical evaluation, we focus on automatically assessing the task of sewing in parallel next to a given guideline. This directly mimics the skill of keeping a consistent seam allowance by sewing cleanly within a given distance

ID	Factor
	Assessing skills of a person
F1	Working with a sewing machine
F1.1	Sound
F1.2	Speed
F1.3	Handling the sewing machine
F1.4	Body Posture
F2	Knowledge
F2.1	Identify source of errors
F2.2	Theoretical knowledge
F3	Working independently
F3.1	Required help
F3.2	Choosing more challenging projects
F3.3	Generating own ideas
F4	Logical skills
F4.1	General logical skills
F4.2	Spatial visualization ability
F5	Manual dexterity
F6	Soft factors
F6.1	Motivation
F6.2	Talent
	Assessing quality of a sewed product
F7	Processing
F7.1	Details
F7.2	Cutting
F7.3	Inner finish
F7.4	Ironed
F8	Seams
F8.1	Seam quality
F8.2	Seam allowance
F8.3	Trimmed seams
F9	Used materials
F10	Functionality
F10.1	Fit
F10.2	Pure functionality
F11	Overall impression

Figure 1.1: Factors of assessing sewing skills of a person and the quality of a sewed product derived from interviewed sewing professionals Rahm [2022]

to the end of the fabric. The seam allowance, also called inlays, describes the distance between the stitching line and the fabric edge to keep while sewing. Keeping a consistent distance to the seam allowance depicts an essential skill in sewing. Analyzing one's ability to do so gives us insight into their level of expertise in this handcraft.

Implementation of a skill-focused iOS application for assessing users' ability to sew along a seam allowance

In this thesis, we propose a ready-to-use application for iOS comprising our research focus on the development of a skill-based assessment. Supported by the conclusions of Rahm's work, we are able to directly continue her research on automated evaluation in personal fabrication. For this, we aim to evaluate the seam allowance which is mentioned as one factor indicating the quality of a sewed product and hence the level of expertise of the sewer. The practical part of this thesis included testing several image recognition approaches and gaining insight on their different outcome on which we eventually decided on a suitable solution. We conclude that using color detection for determining the seam and printed line in images works best as we are able to extract detailed features regarding the shape of the objects. Additionally, we apply coarse registration, typically found in 3D image mapping, for comparing relevant lines for similarity Díez et al. [2015]. As a result, our application returns two insightful analytical values, the *replication accuracy* and the *distance consistency*, to measure users' completed task of replicating the given line. We present our implementation by describing the core functionalities of our implementation and providing relevant background information. Further, we discuss proper evaluation and skill analysis of the outcome.

Research question

RQ : How can we automatically and directly assess individuals' practical sewing skills by focusing on the aspect of the seam allowance?

Chapter 2

Related Work

Our work investigates ways of analyzing user-sewed seams and lines to evaluate the sewer's expertise in sewing parallel to straight, wavy and zigzag lines. To objectively evaluate users' sewing skills for providing individual expertise-fitting sewing tutorials, we concentrate on the properties of the seam allowance that we ask users to sew in parallel to. By using image recognition to identify lines and seams and adapting of coarse registration algorithm to evaluate the result, we propose an implementation aimed to provide immediate feedback.

Fundamental areas of our approach

The literature related to our paper is organized into the following. First, we illustrate our motivation on researching the assessment of handcrafting skills. After that, we give an overview of works focusing on automated skill assessment in physical activities, professions requiring technical competence and lastly personal fabrication. Furthermore, as our solution includes the usage of image recognition to assess users' sewing skills, we identify papers that propose computer vision methods to evaluate manufactured products. Lastly, we compare the mentioned related literature on their content and emphasize the relevance of our work.

Structure of presented related work papers

2.1 Motivations for Assessing Crafting Skills

Growing interest in personal fabrication

With a rising trend of self-production, where a large scale of hobbyists share and are inspired by ideas online Lee and Ocepek [2023], we identify a growing interest group looking for further substitutes and information on their craftsmanship Kuznetsov and Paulos [2010]. Motivations for DIY projects range from economic benefits and a need for customization to the fulfillment of handcrafting and desire for uniqueness Wolf and Mcquitty [2011]. Online communities and platforms offer exchange and advice on a large scale while Makerspaces are physical places for the usage of tools and interaction. The development and adoption of digital tools may enhance the automation and convenience of crafting at home. Therefore, by contributing to the maker community with an automated skill evaluation, we offer a novel approach to further aid regarding self-assessment and future projects.

Home sewing with high popularity

With a global revenue reaching 1.5 trillion U.S. Dollars in 2022 Smith [2023], the apparel market stands as one of the world's largest industries. At the same time, home sewing maintains its popularity. In a study by Martindale and McKinney [2020], investigated motivations for women engaging in personal garment production include achieving optimal fitting, ensuring better quality, and deriving personal fulfillment. The presence of online communities, such as the Reddit online sewing community[1] with 1.2 million users as of November 16, 2023 Reddit, and the 0.76 million readerships of the sewing magazine Burda Style[2] in 2021 Media [2021], indicate a consistently high level of interest in home dressmaking. This suggests that, despite the dominance of the clothing industry, home sewing remains relevant for a large number of individuals.

Continuation on developing an automated sewing skill assessment

This thesis continues Ricarda Rahm's exploratory work on proposing automated skill classification tools for hobby sewers Rahm [2022]. The author interviewed 10 professionals in the field of sewing about techniques on

[1] `https://www.reddit.com/r/sewing/`
[2] `https://www.burdastyle.de/`

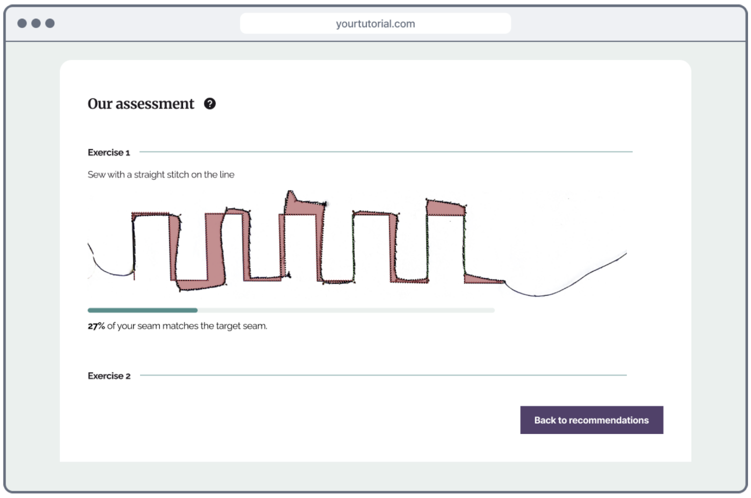

Figure 2.1: Prototype of a web page shown to the user after the upload of the photographed sewing task. The result of the exercise involving the sewing onto a given line is evaluated by the system and visually depicted for the user on the screen Rahm [2022].

how to assess the quality of a sewed object as well as a person's expertise in this handcraft. Besides testing theoretical knowledge via a questionnaire, Rahm theorizes an application to assess sewers' practical skills that our work refers to. In this task, the user is asked to sew on as well as along lines printed out on a sheet of paper. After uploading an image of the resulting seams via smartphone, the user receives the evaluation on the web page of the skill assessment. Figure 2.1 shows the prototype of the web page view of the evaluated exercise as proposed in Rahm [2022]. Here, the user was asked to sew on the given line. The rose-colored areas mark the differences between the stitched result and the given pattern, whereas the computed result, a score of 27%, is displayed underneath.

Based on Rahm's findings we are able to directly continue realizing part of the envisioned prototype by concentrating on evaluating sewers' ability to sew in parallel next to a given line.

2.2 Automated Technical Skill Assessment

Practical skills contain multiple aspects and the evaluation of those often requires broad observation

Since our ultimate goal is to give the user helpful feedback for their sewing skills to eventually recommend matching sewing tutorials, our work aims for a user-oriented application. Apart from simple questionnaires, there has been no research to our knowledge in automated sewing skill evaluation yet. Rating a person's practical skills in a distinct area often requires a broad observation regarding several different details of the field to evaluate their level of expertise. This is confirmed by works gathered in the following that assess individuals' expertise in different practical areas while often using sensors or computer vision.

2.2.1 Physical Activities

Accurate data depiction and encouraging feedback as motivation for users in personal fitness tracking

Automated productivity evaluation of physical activities has become popular over the last years with the help of smartwatches and mobile applications tracking the wearer's movements and physical condition. In their study, Asimakopoulos et al. [2017] investigated how fitness apps influence users' motivation to continue with physical activity. They concluded that motivational feedback appropriate for their performance as well as accurate sensing data were amongst other things having a high influence on users' motivation. Future work could investigate whether encouraging feedback on correctly classified outcomes may also have an impact on users' motivation to carry out sewing tasks.

Real-time feedback privileged for automatic assessment in elite sports

In Giblin et al. [2016] authors evaluated the impact of monitoring systems providing feedback to elite athletes in competitive sports. Different techniques, such as motion capture to observe participants without movement restraints while practicing, or force plates, that measure the ground reaction forces of a person standing on them, are mentioned as effective in data collection but are considered as time-consuming. To be able to provide real-time feedback is stated as an important factor of an evaluation system due to athletes' tight and time-consuming training schedules.

Consequently, at present, several solutions are tracking factual physical activity via self-assessment and providing related feedback to the user. However, fewer concentrate on the perceived skill level of individuals. Ladha et al. [2013] propose a wearable analysis system sensing climbers' movements and classifies the detected climbing performance based on a scoring scheme. By testing their application on 53 participants, the authors demonstrated their automatic analysis approach yielded a correlation of 0.74 to human-rated scores of the participants' climbing performance.

Wearable device classifies climbing skill of users with sensors

2.2.2 Technical Profession

While most forms of handicrafts are also commercial activities, there are further practical skills limited to the respective field of profession. Surgical procedures comprise separate skills including instrument handling, suturing and knot-tying. There are multiple research works concerning automated skill assessment in practiced surgery. Levin et al. [2019] collected and compared several papers investigating methods of evaluating proficiency in this technical profession. Researchers either use computer vision techniques or sensors to capture hand, tool and eye motion. Additionally, machine learning, deep learning methods or classifiers are used to evaluate the performer's surgical technical skills. The authors attribute the automatic systems to eliminate existing bias in human rating. Relating to our work, our objective assessment aims for an unbiased skill evaluation as well.

Computer vision and sensors to observe surgeons' practical skills

2.2.3 Personal Fabrication

In Gong et al. [2019] researchers used sensor data to train a model to predict and recognize user identity, expertise and fabrication activity in the field of woodworking from a set of 14 participants. Figure 2.2 shows the statistics of

Research on determining identification, skill and skill level with machine learning

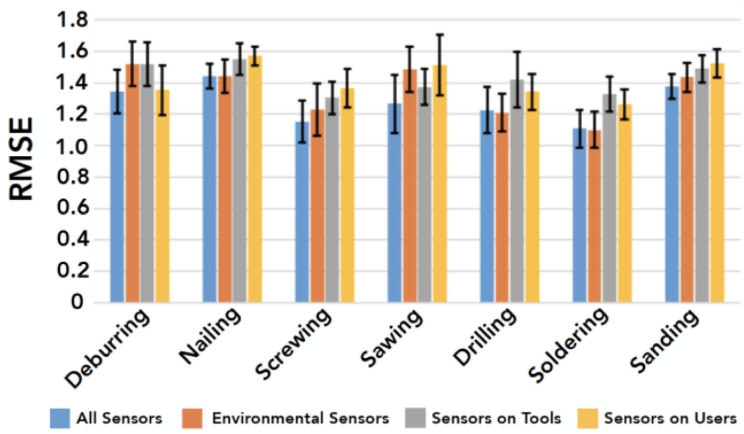

Figure 2.2: Evaluated leave-one-out results for each woodworking task using root-mean-square error Gong et al. [2019].

the achieved results for skills classification using the root-mean-square error (RSME) and Random Forest Regressor as the model for expertise inference. The sensors used for identifying the expertise of the participants in each task are subdivided into environmental sensors, sensors attached to tools and sensors attached to users. The resulting leave-one-out classification yielded an overall average RSME of 1.27, which was not enough to classify users' expertise precisely, but sufficient to distinguish beginners from experts in the respective field and similar to the ratings done by two experts.

Machine learning models require prior training

The authors therefore prove that the instrumentation of users and their tools in an established environment is able to rate the individuals' handcrafting skills similar to humans. However, they admit to the simplicity of those tasks they tested as well as the versatile classification of users' skills. Further, using machine learning to first train the model on recognizing individuals and their expertise is a complex process consisting of multiple steps and not optimally feasible for the quick and simple skill evaluation that we aim for.

Relative skill classification from tutorial videos

Doughty et al. [2018] developed methods to determine relative skill from tutorial videos by ranking the observed tasks including origami folding or omelet making using a pairwise deep ranking model. Their system achieved over 70% accuracy in correctly comparing the skill levels shown in the tutorials which include dough-rolling and chopstick-using. Similar to our goals of developing a helpful guide for makers, the authors' goals also comprise the improvement of suitable instructions as well.

2.3 Computer Vision for Product Evaluation

Automated product evaluation dominant in industrial manufacturing

To evaluate the practical sewing skills we analyze the sewed seam of a user using image recognition techniques. Instead of directly tracking the act of sewing itself, we evaluate aspects of the finished product crafted by the user. We have not found work studying the features of handmade products using computer vision techniques. However, a considerable amount of research concentrates on automating the inspection of both food quality and manufactured apparel for the industry. Contrary to our motivation, these solutions do not aim for skill classification of the producing party but for simple review or quality control.

2.3.1 Agricultural and Food Products

Computer vision for color and defect sorting of food

Brosnan and Sun [2002] provide a comprehensive review of current techniques used for inspecting and grading agricultural and food products. The authors point out the presently wide usage of computer vision technologies within the food industry, possibly due to its cost-effectiveness and efficiency. The mentioned techniques range from neural networks to digital image analysis methods and predominantly concentrate on physical properties, such as color, as well as mechanical damages of the products. Further goals include optimum handling and storage equipment.

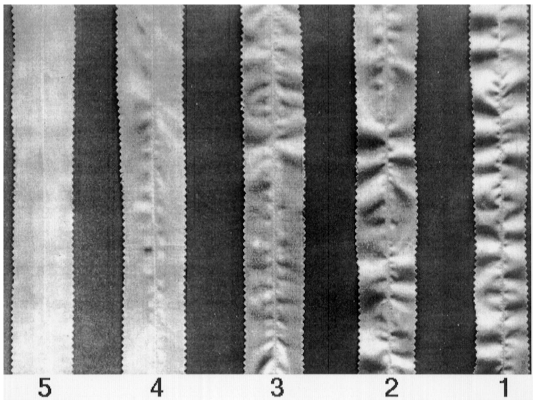

Figure 2.3: The depicted examples show how experts rate the seam quality manually which are used as reference for depicting the waviness along the seam Bahlmann et al. [1999].

2.3.2 Fabrics and Seams

Computer Vision on fabrics concentrate on seam and stitching defects in industrial manufacturing

Related works on image recognition in the context of textiles heavily focus on determining seam quality and detecting flaws in industrial manufacturing. Since quality control in the apparel industry is widely performed manually which makes the procedure time-consuming and cost-intensive, several research works propose an automated approach. Solutions on detecting defects of post-production include the wavelet transforms Ngan et al. [2005], as well as neural networks Bahlmann et al. [1999]. Figure 2.3 illustrates the identified differences used to manually examine the seam specimen, as described in Bahlmann et al. [1999]. Textile experts use these distinctions to differentiate the smoothness of the seams with ratings ranging from 5 for a properly executed seam to 1, a seam with high waviness. The system utilizes a neural classifier to evaluate the property of seams in grey-value images based on the expert guide, achieving an 80 percent accuracy in correctly classifying these seam types.

Different motivation between our work and related work

As the motivation of these works focuses on the finished end product for commercial purposes the main emphasis of their research is different from ours. Instead of skill assessment, the presented related works consider the smoothness of the fabric, broken fabric or missing yarn.

There is no work found that specifically addresses the seam allowance as typically, in industrial textile manufacturing, this feature does not appear as an issue to be looked into further. So while there is extensive literature on the usage of computer vision methods to classify a sewed product, the works are limited to determining possible flaws of the end product. Contrary to this, the aim of our work is to analyze the end product to gain information about the sewer's level of expertise. However, further research could include an investigation of whether examining these flaws as done for industrial manufacturing could also applied to indicating one's sewing skills.

Related works do not take into account sewers' skill level

2.4 Comparison of Related Work

In this concluding section, we present a comparative analysis of the content from the related work mentioned above. We demonstrate the connections from our paper to the literature, illustrate the position of our paper within the field and highlight how it addresses existing research gaps.

Similar to Ladha et al. [2013], Levin et al. [2019] and Gong et al. [2019] our main goal is the automatic evaluation and its following classification of practical skills. We validate the need for our application by previously conducted experts' opinions, as we derive from Rahm [2022], and the concluding definitions of levels of expertise in the respective fields. By observing relevant properties of the given tasks or actions our systems are able to rate users' skills objectively. As the automatic assessment of practical sewing skills has not yet been further explored, we give an example of how this can be achieved by examining sewed seams parallel to the seam allowance. However, though we also utilize visual observation, unlike the mentioned literature we do not use machine learning or deep learning techniques which require a profound data collection and training beforehand and are partly tied to individuals. Instead, as our handcrafting field allows us to do this, we directly observe the finished product and not the actual practice.

Main goal is automatic skill assessment

Computer vision to evaluate properties of products

The observation of the seams and lines is done by image recognition methods, precisely color detection. Ngan et al. [2005] and Bahlmann et al. [1999] also identify properties of seams in sewed products with the help of computer vision algorithms. But, instead of aiming for information of the sewers' level of expertise, their research concentrates on the detection of flaws in the stitching. Brosnan and Sun [2002] list works that utilize machine vision for food grading to sort agricultural and food products by their quality. In contrast to our work, the systems proposed in the aforementioned related literature require training before they can effectively classify the desired properties.

Table 2.1 shows an overview of the contents of selected related literature and our work. The table highlights the different motivations, fields of application and whether the proposed approaches are directly applicable without previous training.

	Skill Assessment	Handcrafting	Direct Appliance	Field
Levin et al. [2019]	✓	✗	✗	surgery
Ladha et al. [2013]	✓	✗	✗	climbing
Gong et al. [2019]	✓	✓	✗	woodworking
Doughty et al. [2018]	✓	✓	✗	everyday life
Chan and Pang [2000]	✗	✗	✗	sewing manufacturing
Our paper	✓	✓	✓	sewing

Table 2.1: Overview of comparison of related research work in terms of content

Goal of this thesis

Given the growing number of makers, we want to contribute to the sewing community by exploring methods of evaluating users' practical skills in this field. Due to our directly applicable image recognition method and matching algorithm, our system is able to work without prior training. Further, an automatic sewing expertise assessment enables an objective, fact-based analysis for users wishing to gain insight.

Chapter 3

Background

In this chapter, we introduce relevant background information about the principles we adapt to track users' sewing skills. First, we cover findings about classifying sewing skills, as explored in Rahm [2022], on which we form the foundation of our subsequent work. Following this, we briefly describe the fundamentals of coarse registration, an alignment method for graphical components, which we use for matching and comparing the seam with the printed line.

3.1 Sewing Skill Classification

Practical sewing skills are based on multiple factors

In the following, we give an overview of the investigated aspects of sewing skill classification in Rahm [2022] on which we build our application. In the author's interviews with sewing professionals, she extracted multiple features of the finished sewn product that can be evaluated to determine one's level of sewing expertise. The task of evaluating users' seams is derived from the interviewees' answers on how to assess the quality of a sewed product. Evaluating such gives sewing experts indications of the sewer's expertise. In addition to assessing seams, evaluated factors include the processing, the materials used, the functionality and the overall impression of the product. Properties of the seam especially comprise seam lengths and the correct width of the seam allowance. Due to our focus on assessing users' proficiency in consistently sewing alongside a guiding line to mimic the seam allowance, we will now provide a brief description of this particular aspect.

3.1.1 Seam Allowance

Properties of an accurate seam allowance

The seam allowance is the distance, usually around 1cm, kept from the stitching line parallel to the fabric fold or respectively the selvage. It ensures a clean as well as functional finish for the garment. When using sewing patterns, based on the wearer's body measurements, the width of the seam allowance is correspondingly added to the given pattern lines. Important factors of the seam allowance, indicated by sewing experts in Rahm [2022], are an adequately chosen distance width and a consistent parallel stitching line.

Sewing with seam allowance is an indicator for sewing skills

We use Rahm's findings about ways of classifying sewing skills to directly apply her ideas to our practical approach to realizing the skill assessment. Consequently, we take over the aspect of the seam allowance which is stated as relevant in sewing and an indicator of an individual's practical sewing expertise. Our derived task tracks parallelism, which assesses the consistency of the distance maintained between the user-stitched seam and the given line.

3.1.2 Task of Parallel Sewing

User's task and evaluation of the system

Building on findings and a tutorial prototype suggested in Rahm [2022], we developed an automated system for evaluating users' technical sewing skills, specifically regarding their ability to sew parallel next to a guiding line. As described in 2.1 "Motivations for Assessing Crafting Skills", Rahm's prototype involved the assessment of parallel sewing onto a sheet of paper with indicating lines. The application afterward evaluates the sewn seams and provides feedback on the overall accuracy achieved in the task. With our work, we realize part of her ideas involving the practical sewing evaluation.

3.2 Coarse Registration

In our application, we adapt the principles of coarse registration to match lines onto each other and thus evaluate their similarities. Coarse registration tries to find the best match between two geometric components by systematically positioning one component onto the other to measure shape similarity. By moving the seam onto the guiding line, we are able to compare their shape based on their distance to each other and the percentage of overlapping points. The fundamentals of coarse registration described in this chapter later help in understanding our adaption of this approach.

Coarse registrations enables line comparison

Coarse registration is a favored method in 3D object matching, often using point clouds or meshes as a reference to reconstruct a 3D sculpture based on captured photos of the subject Díez et al. [2015]. The algorithm returns a final alignment, determined by identifying the closest match with the highest similarity between the input components.

Coarse registration used to match images of 3D objects

After collecting or receiving the input data, the algorithm systematically tests different alignments and compares these based on a predefined distance metric, often measuring the two entities to match, after each newly registered position.

Alignments are rated based on the current distance between components

To evaluate the tested positions a suitable distance metric is needed. For our application, we utilize Chamfer distance, which is based on nearest-neighbor computation and a standard metric to measure shape similarity between point clouds by approximation. Historically, the chamfer distance was developed from Chamfer matching, a technique in image matching to compare the shapes of objects Barrow et al. [1977]. Given two point sets A and B, the Chamfer distance from A to B is calculated by summing all distances from each point of A to their respective nearest point in B. This metric thus provides a straightforward way of calculating the overall distance between two objects. The resulting alignment therefore is determined by the position with the lowest yielded Chamfer distance during testing.

Chamfer distance as distance metric to evaluate tested positions

Chapter 4

Design and Approach

Structure of the presented design and approach of our application

Due to the focus of this thesis on the practical development of an application, in this chapter, we provide a detailed description of its design, adapted features and our process of finding suitable methods. We first present an overview of our design methodologies by describing the required steps of the user's task and the workflow of our application. The following subsections are structured to mirror the design of our implementation. Starting with the input image uploaded by the user, which includes the sewn seam alongside the printed line, our system first identifies these relevant elements. Subsequently, it analyzes the features of the determined seam and provides a rating for the result. Our discussion therefore begins with an exploration of the methods we found most effective for line detection in an image. Following this, we reflect on our process for selecting an optimal line-matching technique, which is important for evaluating the properties of the seam. Finally, we propose the evaluation metrics our system computes to provide users with insightful feedback.

Term conventions

Throughout our text, we refer to the line that is depicted in our given pattern to print out on a sheet of paper as *printed line*, *given line* or *guiding line*. Further, we refer to the seam that the user is asked to sew next to the printed line as *sewed line* or *seam*. Both lines are not necessarily straight but can also be wavy or in zigzag shape.

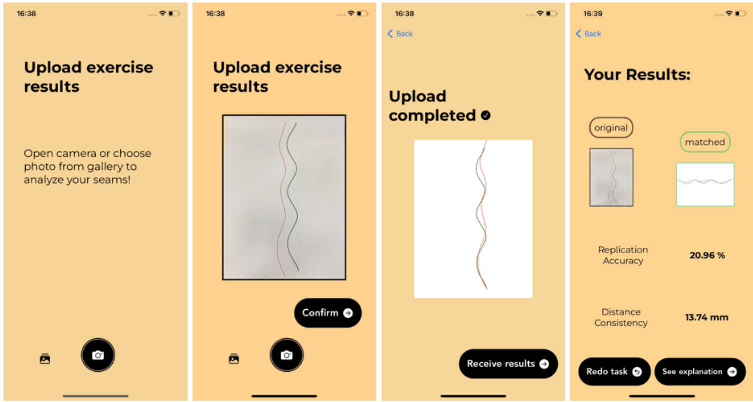

Figure 4.1: Workflow of the application comprising the photo upload and evaluated results.

4.1 Assessment Workflow

Based on our designed skill assessment, we developed an application that guides users along the task and eventually provides them with the evaluated result.

Practical task The task given to the user is proposed as follows.

1. Printing out the provided pattern in color
2. Sewing onto the sheet of paper next to the printed line with the specified-colored thread in an indicated distance
3. Taking a photo of the result and uploading it to the application

Application workflow The screenshots in Figure 4.1 show the workflow of the application that is visible to the user. The user is asked to take a photo of the finished task or choose it from the gallery. After confirming the chosen image, the matching algorithm is run and first returns a visual depiction of the matched lines. The next view then shows the evaluation page with the original taken image, the matched lines as well as the two analysis variables.

4.2 Identifying Lines and Seams

Computer vision algorithms help to detect content in an image

In the context of our sewing task, accurately detecting specific features within the input images is crucial. Computer vision techniques help us identify desired objects in an image. The online programming library [1] (Open Computer Vision) offers a wide range of ready-to-use algorithms, specifically designed for image processing and computer vision tasks. Given the detail of the fine-printed lines and seams, we aimed for a solution that is able to identify the shape of a line down to the millimeter and therefore provide information on the detected components.

Image processing conventions adapted to our goal

In computational image processing, images are generally represented as matrices, where each element corresponds to a pixel. These matrix elements store values based on the RGB (Red-Green-Blue) color model. By manipulating these values, we are able to modify, analyze, and interpret visual data effectively. As a result, we store captured components, which are the lines, as arrays with each array comprising the pixels that form the specific components. By examining these pixel arrays, we are able to derive and subsequently present evaluation values that offer insights into the properties of these components.

Structure of the proposed object detection technique and alternatives

In the process, we concluded that the typical familiar image recognition algorithms used for different kinds of object detection do not seem suitable for our application. In the following, we first describe the technique we used for detecting the seam as well as the printed line. Afterward, we provide an overview of additional line detection algorithms that we explored but found to be unsuitable for our application while testing.

4.2.1 Color Detection

Color detection for precise line detection

While testing different computer vision algorithms, we found that color detection was the most effective method for correctly identifying lines of detail and particularly cap-

[1] `https://opencv.org`

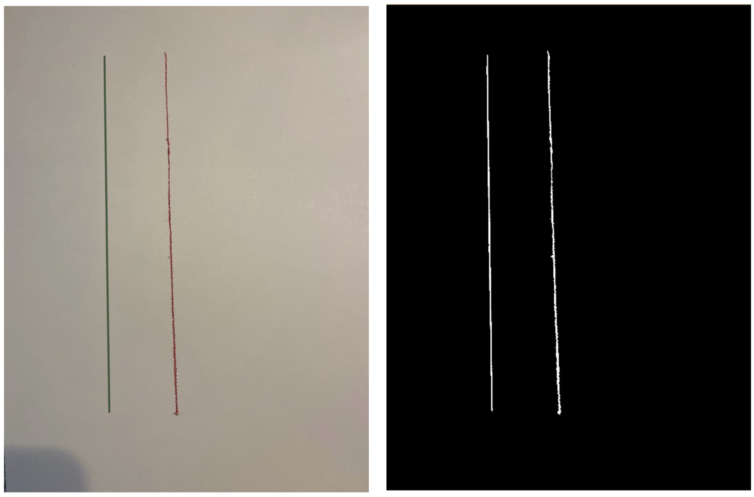

Figure 4.2: Detection of the printed line and seam using specified HSV color ranges for red and green shades.

turing their shape. Color detection checks for each pixel individually whether its value is included in the defined input range. This way the algorithm is able to depict a pixel-accurate representation of the lines found. As a result, by using color detection to identify each line it is essential to make sure that we use a different colored thread for sewing the seam line and printing the given line to differentiate between the two.

Application of color detection to store shape and placement of line and seam

We use OpenCV's `inRange()`[2] function that checks whether a pixel is within the passed HSV (Hue-Saturation-Value) range. After determining the printed line and the seam in the image matrix we store each component in an array consisting of their associated pixel coordinates. To decrease computational complexity while iterating over the arrays we only use every first found pixel in each row as feature points in the following coarse registration. We will elaborate on this further in 4.3.4 "Reducing Array Sizes". Given our presented patterns only include vertical sewing orientation this does not impact the result.

Visual representation of the usage of color detection to identify printed lines and seams

Figure 4.2 illustrates the input image on the left and both the printed line and seam identified by our implementation

[2] https://docs.opencv.org/3.4/d2/de8/group__core__array.html#ga48af0ab51e36436c5d04340e036ce981

on the right. We defined two separate masks for the green printed line and the seam sewed with red thread. The algorithm marks any pixel falling within these HSV ranges by setting it to white against a black background, as displayed in the output image on the right. As a result, the shape of the seam and the printed line are likewise precisely reflected.

4.2.2 Alternative Approaches

Several tested object detection algorithms did not yield satisfying results

In the process of finding suitable methods that help us not only identify subtle structures in an image but also compare those in their shape, we tested several object detection algorithms which eventually have not proven applicable. Our initial instinct of using feature extraction approaches for our line detection has proven insufficient. In the following we describe these algorithms, how we applied them in our implementation and how they differ from the desired result.

Generalized and Probabilistic Hough Transform

Hough Transform for line detection yielding varying results

The Hough Transform[3] (HT) is a shape detection algorithm and originally implemented for detecting straight lines but adaptable for determining further simple geometric shapes Hough [1962]. The HT is implemented on a binary image after preparatory edge detection, making the adjustment of parameters for both edge detection and the HT critical for optimal feature detection. Clearly discernible edges often lead to the recognition of multiple objects, which can distort the intended result.

HT insufficient for precise shape analysis

Prior to applying HT, we preprocess the input image to reduce complexity as well as noise and contrast. This is achieved by greyscale conversion, Gaussian smoothing and Canny edge detection. HT then looks for the defined

[3] https://docs.opencv.org/3.4/dd/d1a/group__imgproc__feature.html#ga46b4e588934f6c8dfd509cc6e0e4545a

features of the detected edges in the binary image. We tested both the generalized and the probabilistic HT which both failed to exactly detect and replicate all original lines precisely. Although an adaption of the probabilistic HT yielded more accurate results as the general HT showed problems in determining objects within low-contrast images, both algorithms were not suitable for our application. Identified lines yielded by these methods are made visible in the output image with a colored line overlaid at its approximated position. These displayed lines do not optimally represent the determined lines in the image but rather document the mere existence of these. For our application, it is therefore not sufficient to receive only the vague graphical orientation of the wanted lines as we are not able to compare features between our lines without a detailed or exact replica. needs adaption for each example to yield the right amount of lines In conclusion, the application of HT serves as a method for the mere determination of lines rather than an exact identification in terms of size and placement within an image.

Output images

Figure 4.3 shows the visual outcome of line identification in two sample images, each featuring green printed lines and red seams, using the probabilistic Hough Transform. In the resulting images on the right, lines detected by the algorithm are overlaid in blue. The small white areas mark the edges identified through Canny edge detection, in which the HT looks for the defined features of straight lines. While our implemented algorithm is able to determine the depicted lines correctly, the approximation is not precise enough. While the seam in the upper left original image is continuously visible, the output image next to it shows that HT only partly recognizes said component. Moreover, the algorithm returns several lines instead of one for each. In each example, the red seam yields more recognized lines than the green printed line. This is distinguishable by a respective thicker blue line, formed by multiple lines in one spot, in the resulting image.

The small white regions indicate the edges identified through Canny edge detection, which the HT uses as a basis for locating straight lines. Despite the algorithm's ability to correctly identify the lines in the images, its accuracy in

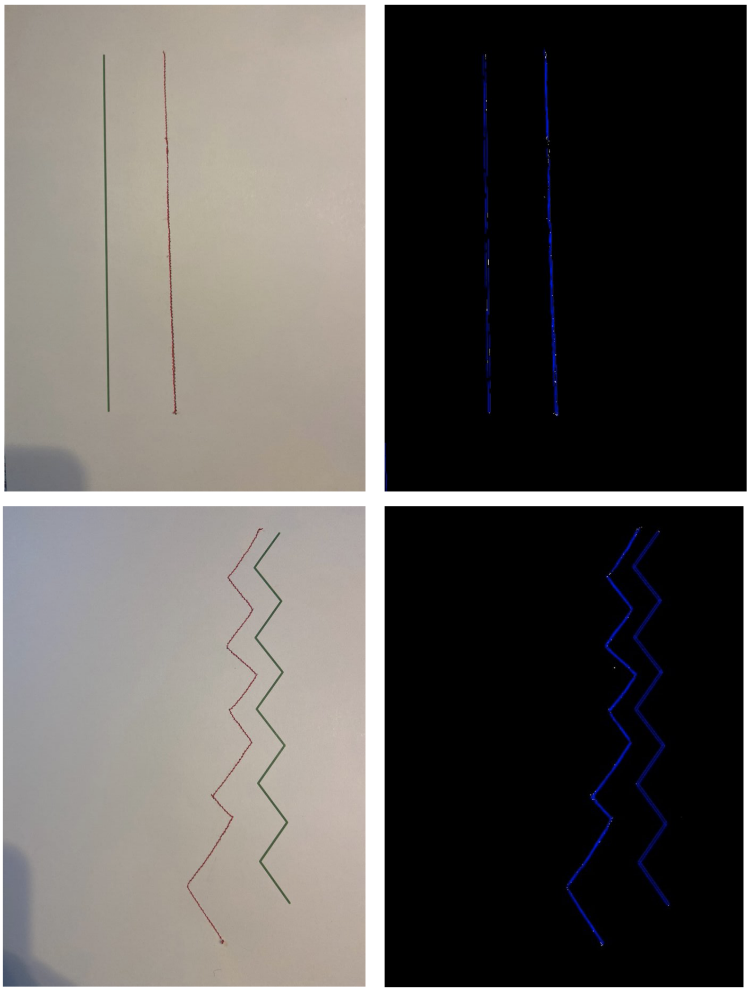

Figure 4.3: Determination of the printed line and seam using the probabilistic Hough Transform.

approximation remains suboptimal. For instance, although the seam in the upper left original image appears continuous, the adjacent output image reveals that the HT only partially recognizes this element. Furthermore, the algorithm tends to detect multiple lines for each seam or printed line, rather than a singular, distinct line. This is evident in the images, where the red seams result in a denser accumulation of blue lines compared to the green printed lines, creating a visually thicker blue line in the output images.

Line Segment Detection

Similar to HT with sole determination of lines

The line segment detection[4] , as described in Grompone von Gioi et al. [2012] works with identifying high-edge density regions and marks these spots with overlaying straight lines on the determined areas on the original image. In comparison to Hough Transform, the Line Segment Detection worked more reliably without much additional adjustment. However, the algorithm is not directly applicable for other than straight lines and, similar to HT, only yields the determination of lines without the precise placement and an accurate reflection of their shape.

Find Contours Algorithm

Returned contours were not as pixel-accurate as color detection and would need further adjustment

Furthermore, we tested the `findContours()`[5] method, as proposed in Suzuki and be [1985], to determine desired content. Here, the algorithm returns highlighted components by marking the edges of visible elements in a binary image. Though our adaption yielded correctly identified lines, the focus of this method lies on the outline of determined elements. Therefore, by utilizing this method we need to implement an additional algorithm for marking the inside of the outlined lines since ultimately only the inside of a contoured line is relevant to us. However, the resulting marks returned by `findContours()` were not as pixel-accurate as the later-tested color detection. Therefore, we did not further integrate its adaption.

Connected Components Labeling

Connected Components labeling to distinguish between the seam and printed line

In earlier versions of our project, we employed the con-

[4] https://docs.opencv.org/4.x/db/d73/classcv_1_1LineSegmentDetector.html

[5] https://docs.opencv.org/3.4/d3/dc0/group__imgproc__shape.html#ga17ed9f5d79ae97bd4c7cf18403e1689a

nected components labeling[6] (CCL) to identify the seam and the guiding line and differentiate them from the background. The CCL works by looking for hard edges within the input image, thereby segregating single objects from a uniform background. We applied the 8-way connectivity, as proposed by Bolelli et al. [2020]. Despite its effective functioning, we found that using color detection proved to be a more efficient method for this particular task.

Combining color detection with connected components algorithm

Initially, we utilized CCL to detect all kinds of features within an image. For this, we extracted the line and seam from the components detected with CCL and afterward used color detection to distinguish between these two relevant objects. We filtered out irrelevant components, such as background noise and edges of the sheet of paper, by eliminating elements identified by the algorithm of which pixel sizes were below a certain threshold size.

Sole use of color detection for the identification of line and seam is sufficient

In the final implementation, we exclusively rely on color detection to identify the printed line and the seam and passing their properties on for line matching. Our experience has shown that applying CCL tended to complicate the process. The sole use of color detection is sufficient for feature identification and does not require an additional step of eliminating irrelevant elements. However, by solely using color detection to identify the lines, deciding on the correct color range defined in the implementation is crucial. Additionally, besides printing out the given pattern sheet in color and using the correct colored thread indicated by the application, the user is advised to have no color shades similar to the printed line or the seam visible in the input image of the photographed result.

4.3 Line Matching

Line matching to determine dissimilarity between the seam and printed line

After determining the printed line and the seam with color detection we store each component in an array consisting of

[6] `https://docs.opencv.org/4.x/d3/dc0/group__imgproc__shape.html#ga107a78bf7cd25dec05fb4dfc5c9e765f`

the coordinates of its respective pixels. Eventually, we want to rate the user's ability to sew with a consistent distance to a given line. This can be achieved mathematically by comparing both lines by their similarity. We therefore align them as close as possible to each other and rate the resulting matching. For the alignment, we apply coarse registration.

Coarse registration for line matching and structure of the proposed process

As introduced in 3.2 "Coarse Registration", coarse registration algorithm looks for the best matching of two objects by testing multiple positions based on a metric indicating the closeness between them. It allows us to eventually compute the ratio of overlapping points of our guiding line and the seam. After we illustrate why and how we are able to apply coarse registration algorithm to our goal of analyzing a sewed line, we proceed with detailed features of our implementation. Here, we document our process of determining the most suitable input data as well as different variations of the algorithm.

4.3.1 Coarse Registration for Line Comparison

Coarse registration enables us to directly compare lines based on their similarity

Coarse registration makes it possible to directly compare the morphology of the seam and the printed line. By aligning the printed line to the seam, aiming for the closest distance between both elements without altering the orientation, we enable not just a visual but a computational assessment of their similarity.

Coordinate points of identified lines as input for coarse registration

In the field of 3D registration, the input data often consists of multiple points that characterize and represent the 3D object. We are able to easily adapt the idea of using single points as reference for our entities by using the coordinates of the pixels that our lines consist of. Therefore, we use the terms *pixels* and *points* in this context interchangeably.

Technical notes on integrating coarse registration within our sewing assessment

Within the framework of sewing in proximity to a prescribed line at a specified distance, that mimics the seam allowance, our objective is to evaluate the user's proficiency in maintaining a consistent distance from the intended shape of the line. Given our patterns are vertically aligned, the ideal outcome would be the seam laying exactly on top of the printed line with maximum overlapping indicating an exact replica of each other. Consequently, overlaying the two provides insights into the user's performance in executing the task of parallel sewing.

In our implementation, we chose the seam as the object to be replaced and matched onto the other object, the printed line. To prevent an incorrect enhancement of the placement of the seam, we only use horizontal and vertical position movements to transform the seam. Typically utilised additional rotations to approximate the alignment are counterproductive. This is due to a possible correction of the position of the seam in relation to the given line.

Details on our applied implementation

4.3.2 Transformed Positions

For aligning the seam onto the guiding line to test the positioned seam, we have to change the pixel coordinates of its vector. As alignment orientation, we choose one pivot pixel each in the guiding line array and seam array. To test the position, we move the pivot of the seam onto the pivot of the guiding line with the remaining pixel coordinates of the seam moving in relative accordingly. This way, we directly guarantee a definite overlapping of both components. Based on the assigned pivot points, we test and compare possible registrations and return the best one. An example of how the positioning is processed is shown in Figure 4.4. Based on a pivot point on the seam, the seam is moved horizontally and vertically onto a determined coordinate point on the given line. (1) shows the initial positions of the blue-colored printed line and the yellow seam. As indicated by the respective green-colored direction arrows, the seam is moved upwards (2) and towards the left (3) accordingly. Following this, it is crucial to find suitable pivot points on the seam and on the printed line to ensure an optimal alignment.

We position the seam by moving it onto an assigned pivot point of the guide line

4.3.3 Chamfer Distance as Proximity Metric

To computationally compare the tested positions, we de-

Application of Chamfer distance for line matching

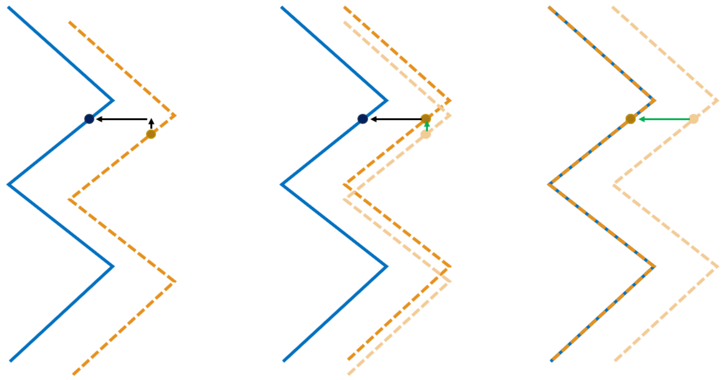

Figure 4.4: Movements based on pivot points on the printed line and on the seam.

cided on the usage of the Chamfer distance as proximity metric, which we referred to in 3.2 "Coarse Registration". The Chamfer distance achieves the highest matching by taking into account the total distance between two elements. The resulting value gives us a general estimation of the proximity between the lines, with a lower value indicating closer matching lines. By finding a position of the seam with the lowest chamfer distance to the guiding line, we get the most accurate overlapping position. For our lines, we are able to utilize their point coordinates as feature points to compute the distance. However, we do not use all points belonging to the respective line and seam identified prior by color detection, which we will elaborate on in the following subsection.

4.3.4 Input Data

Input data impacts time complexity

During the process of implementation we tested different data as input for coarse registration to find the most efficient solution. As the literature on 3D alignment suggests, the input data has the most impact on the time complexity of the program execution Díez et al. [2015]. Large data sets of two components to be matched with may result in high run-time, slowing down the program. As the coarse registration algorithm matches each point from one object with every point from the other by brute force, computations may quickly exceed tolerable numbers. We therefore try to find a way of restricting the number of points to be matched and tested while keeping an accurate final alignment.

Minimizing Input Data

In our implementation, after color detection, the input image gives back an array with pixel coordinates stored inside. This array, the representative of a line, has a highly variable size due to the varying proximity the image is taken from. A wider angle reduces the size of lines in the image, as lines appear relatively smaller in the image, and thus reduces the pixel number forming the lines. Following this, a closer angle causes lines of which arrays store pixel coordinates up to eight-digit entries. This highly increases computation time and is due to an exceedingly high number of position variations to be tested.

Minimization of input points to reduce the number of computations

By choosing the chamfer distance as our measurement during testing the positions for coarse registration, the procedure implies computing the distance of every variation of elements between both arrays. With arrays of sizes n and m this results in $p \times n \times m$ computations of the Chamfer distance after repositioning the seam vector p times. To prevent a high computation number, we tried different approaches to reduce the number of variations to be tested while maintaining accurate alignment results.

Considerably high computation time due to high pixel count

Reducing Array Sizes

In our final version, we decided on reducing the size of the arrays representing the seam and the guide line which automatically results in reduced computation time and complexity. So, rather than selecting specific coordinate points from the arrays, we selectively filter the elements, keeping only those that are relevant. We do this by only choosing every first pixel with the lowest x-coordinate in each row. All remaining pixels forming the line are removed. Doing

Computing chamfer distance between each first pixel in every row so generates an array that consists only of the leftmost pixel in each row forming the corresponding line. The shape of the printed line and the seam are therefore still maintained. Due to this, we users are asked to take images in portrait format for a vertical orientation of lines.

Alternative Approaches

Tested approaches include random pivot selection and systematically using ever s-th point in each array as pivot

Initially, we directly matched each pixel coordinate from one line to the other. This resulted in an exceedingly long computation time. Further testings involved a random pivot point selection on both arrays and dynamically set step variable s determined by a predefined threshold number of tolerable computations. By only matching every s-th pixel coordinate in each array we were able to reduce computations to $n/s \times m/s$. However, as a high number of elements in an array increases the value of s, approximations of the chamfer distance become less accurate due to the reduced and varying distant testing points on the lines.

Description of a graphical depiction of using every s-th pixel of each line to match

Figure 4.5 shows a simplified representation of the described approach of only using every s-th pixel coordinate of each line to align the seam onto the guiding line. In the illustration, the printed guiding line is represented as a blue curve whereas the seam is visible as a stitched orange curve next to it. The far left alignment (1) shows the original positions of both lines with every s-th pixel marked with a circle in each line. The other five alignments next to it represent the process of matching based on the algorithm, whereas (2) and (3) depict the first two tested matching positions and (5) and (6) the last two. The circle marks the pair of points upon which the current matching is based. (4) is the final alignment the algorithm returns based on the closest proximity measured at their positions. Here, the third point of the seam is matched onto the third point of the given line, yielding the best matching result.

Comparison of tested input points

The table below gives an overview of the different tested input points for the coarse registration algorithm. We indicate whether the matching by using the respective input points could be computed in acceptable time (less than

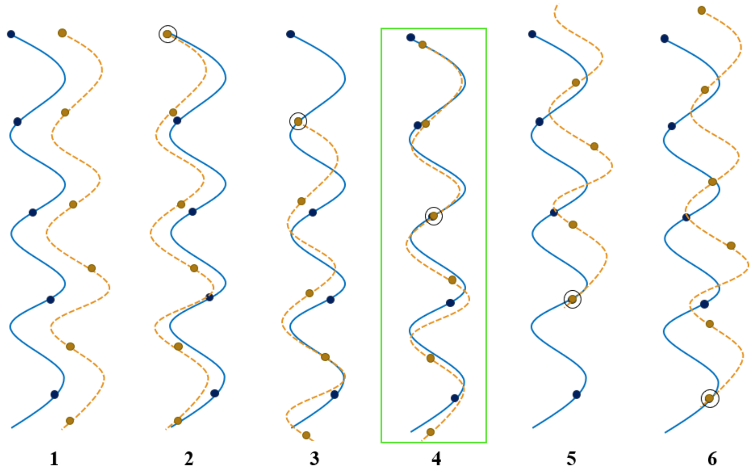

Figure 4.5: Simplified graphical example of the registration procedure using every s-th pixel in each line array to match the orange seam onto the blue printed line. The circles indicate the current matched points of each line. In this example, the algorithm will yield the green-marked alignment as the result.

2 minutes) as well as whether the alignment eventually yielded visually plausible results.

Input points \ Characteristics	Acceptable time	Accuracy of matching
All	✗	-
Random	✓	✗
Every n-th pixel	✓	✗
Defined range	✓	✓

Table 4.1: Comparison of tested input points by their computation time and accuracy of the yielded final alignment.

4.3.5 Optimizing the Alignment Search

Search algorithm significance and dependence on input data

The accuracy of the algorithm used to find the best alignment is closely connected to the nature of the input data. This data, comprising selected pixel coordinates of the seam and the guideline, fundamentally shapes the approach we take in developing the search methods. In the previous subsection, we described our process of improving the input data to reduce computational time. In the following, we want to elaborate on our approach to designing the alignment search itself. While we did this by adapting the insights gained from our previous data selection, both issues were explored hand in hand rather than separately. However, while the alignment search algorithm itself also influences computational complexity, our primary objective here is to effectively achieve an accurate match between the seam and the printed line.

Finalized Search

Searching for alignment around the center of the guiding line is sufficient

Our final solution for aligning the seam onto the printed line consists of matching the seam onto points of the printed line within a restricted range. The specified range is determined by the center pixel of the printed line, on which Instead of matching every point of the seam to every pixel in the printed line, we decided on matching one single point, the center point of the seam, to a specific range within the printed line. This refinement enhances efficiency without compromising the effectiveness of our alignment search. We derive that testing the alignment of the seam along the whole length of the printed line is not necessary as well as misleading as it would be an incorrect portrayal of the placed seam. Consequently, there is no necessity to match the seam to the guiding line at every possible position along its shape. Instead, we try to find a matching point at approximately the same height as the seam.

Description of coarse registration with figure 4.6

Figure 4.6 illustrates our finalized approach of finding the most suitable matching of aligning the seam onto the guiding line in an example of two continuously wavy curves. The printed line is depicted as the blue curve and the seam as the orange stitched next to it. The alignment on the far left (1) shows the initial positions as passed in the original input image with a given printed line and an exemplary stitched seam on the right next to it. The black circle on the orange seam marks the center of the seam line, which also determines the middle of the range on the printed line. The dark blue marked area on the blue guide line high-

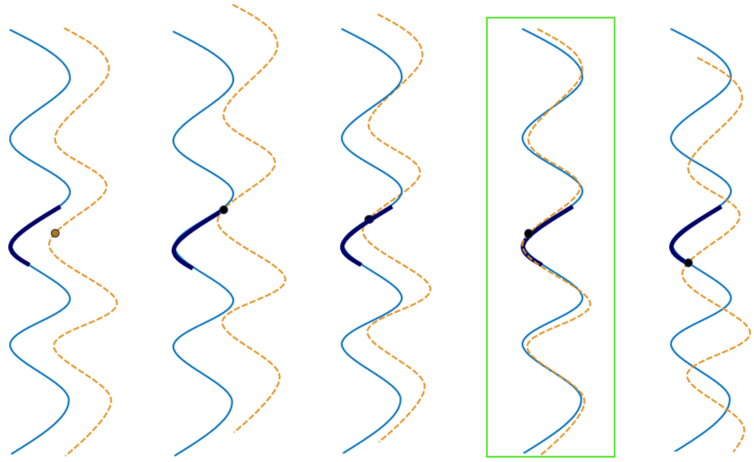

Figure 4.6: Simplified graphical example of the final registration procedure using a range on the printed line determined around the center of the seam (marked as a full circle). The algorithm places the seam onto each pixel in the range and yields the green-marked alignment as a result.

lights the range on where the center point will be matched. (2) shows the first matching tested with the center point of the seam matched onto the first point of the defined range on the guiding line. The remaining alignments (3-5) illustrate the procedure that tests every matching of the center point of the seam onto each point of the pixel range of the guiding line while computing the chamfer distance of each matching. Here, (5) shows the last tested alignment. The alignment marked green (4) is the matching the algorithm returns as it yields the shortest chamfer distance.

Benefits of aligning near the center

Therefore, we eventually only match both lines in a restricted area around the center of the printed line. This helps to keep the computations of the Chamfer distance to r with $r \ll n \land r \ll m$, with r being the number of elements in the defined range and n and m the array sizes of the respective lines.

Alternative Approaches

Initial approaches were directly derived from the characteristics of tested input data

We tried various combinations of adjusting input data, transformations and matching procedures. Our initial strategies regarding the alignment search were directly dependent on the characteristics of the input data we initially tested. Therefore, we started by matching each point of the printed line with every point of the seam. In the subsequent approach, the process was modified in response to the altered input data. We adapted our method to match only every s-th pixel of the printed line with every s-th pixel of the seam. However, both of these methods added unnecessary complexity to the alignment search, as elaborated before.

Single consistent pivot point in the seam to match liens

We drew that for alignment testing, it is sufficient to have one consistent point in one object that is matched onto all points of the other object. Therefore, we minimized our algorithm to use just one pixel from the seam, matching it to every pixel of the printed line. This approach does not only yield the same results as using all pixels of the seam but also significantly reduces the algorithm's complexity, scaling it down to the size of the seam array. Ultimately, we further minimized the complexity as well as the accuracy of this algorithm. Instead of matching a point of the seam to every pixel in the printed line, we now match it to a specific range within the printed line. This refinement enhances efficiency without compromising the effectiveness of our alignment search.

4.4 Skill Analysis

Objective resulting variables as feedback

An insightful skill analysis does not only guide our assessment application to recommend skill-fitting tutorials in the future. It also helps in reflecting the user's current skill level and possible issues to keep in mind. By giving helpful feedback the user is presented with an objective evaluation of their skills. With our application, we solely focus on the result of the specified task. We defined two variables, the *replication accuracy* as well as the *distance consistency*, to indicate the evaluated result of the given task.

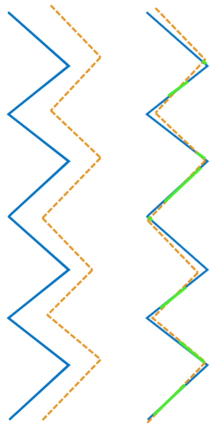

Figure 4.7: Graphical depiction of the green-marked overlapping points after the alignment. The percentage of overlapping pixels within the printed line in blue yields the replication accuracy.

4.4.1 Replication Accuracy

Shape similarity evaluation

Aligning the seam onto the printed line helps us for comparing their similarity whereas a high matching score indicates an accurate parallel seam. For this feature, we defined the replication accuracy. The replication accuracy determines how well the lines match each other both in terms of shape and size. This metric is computed by determining the percentage of overlap between the guiding line and the seam after the resulting alignment. A high replication accuracy, up to 100 percent, therefore indicates a perfect matching and thus a precisely parallel sewn line.

However, this value does not give back further information about the distance the user has kept to the guiding line while sewing. Therefore, we compute another value, the distance consistency, to indicate whether a constant distance was ensured.

Figure 4.7 graphically shows how the replication accuracy is computed. (1) depicts the original placement of the blue printed line and an orange seam, whereas the green areas in the alignment in (2) reflect the overlapping pixels.

4.4.2 Distance Consistency

Focus on consistently sewn distance

While the replication accuracy gives back the user an overall rating of the similarity between the guiding line and the seam, the distance consistency emphasizes the steadiness of the distance maintained during sewing. Maintaining a consistent distance is critical when sewing with a seam allowance, similar to the task our users face when following the pattern line, which acts as our transferred seam allowance.

Measured in millimeters, this metric calculates the average deviation from the mean distance maintained relative to the printed line. A value close to 0 suggests a near-perfect consistency in maintaining this distance.

Computation of distance consistency

We compute the distance consistency by determining the standard deviation of the initial distances between corresponding points on the seam and the printed line. We then convert this calculated distance into millimeters by applying the pixel length of our measured distance to the pixel-to-millimeter ratio of our pattern. This process yields an objective and practical metric that reflects the user's precision in maintaining a consistent seam allowance.

Chapter 5

Implementation

This chapter gives an overview into the specifics of our implementation, which is provided on GitLab[1]. We focus on the back-end application including its structure and underlying logic, to offer deeper insights into the technical aspects. Additionally, to ensure a seamless adaption and continuation of our project, we provide essential guidelines for future developers looking to modify or further develop our code.

Content of the proposed implementation

5.1 Tools and Technology

We developed our seam allowance exercise using the iOS development environment XCode[2]. To handle image processing, we integrated the free and open-source OpenCV library into our project. Consequently, the segments of our code that utilize OpenCV functions are written in a designated separate file in C++, while the front-end functionalities are defined in Apple's Swift language.

Utilized Software tools and languages

[1] https://git.rwth-aachen.de/i10/thesis/thesis-judith-ernstberger-sewing-tracking/-/tree/develop2?ref_type=heads

[2] https://developer.apple.com/xcode/

5.2 Developer Guide

Structure of the proposed fundamentals of our implementation

To start with the development with OpenCV, specifically in XCode, we indicate some fundamentals. As our focus lies on the definite functioning of our skill assessment, our guide does not further mention specifics of the integrated user interface. To ensure a quick understanding of working with the library we provide some basic of image processing to guide future developers. Further, we specifically indicate adjustable variables and settings of our implementation.

5.2.1 Integration of OpenCV in XCode

Core functionalities implemented in Objective-C++ Wrapper file

The integration of OpenCV in XCode is ensured by adding a bridging header besides including the framework within the desired project. The back-end code using algorithms of OpenCV can now be written in C++ in a Wrapper file that is able to compile both code in Objective-C and C++ languages and is linked to its header. The front-end code of our application including the views is implemented in XCode's language Swift.

5.2.2 Image Processing

Images are stored as matrices

An image is typically processed as a transformation matrix, whereas the size of the rows and columns is equivalent to the pixel resolution. Further, the color value of each pixel is stored in the passed matrix of the image and thus can be accessed and modified. Here, the values can have different formats based on the type of the image, HSV, binary, RGB. When addressing pixels, their position is indicated by their position in the matrix, with the leftmost upper pixel being in row and column 0.

Color space conventions

Additionally, we note that the typical order of the color convention code RGB is reversed when applying OpenCV functions in XCode, thus resulting in BGR. The relevant consequences include a reversely assigned order of color codes when referring to RGB and HSV color space, resulting in switched values e.g., red and blue.

5.2.3 Adjustable Settings

We integrated some global variables for direct adjustment that are relevant for an adapted usage of our application. These can be found in the global declaration section at the beginning of the `Wrapper.mm` file of our code project.

HSV color ranges for seam and line detection

The colors to be detected are defined in the HSV color ranges. Our implementation allows direct color adjustment by setting the desired HSV color space in the global declaration section. In our current version, the color of the printed line to be detected is set as green whereas the seam is set as red.

```
Scalar LOWER_PRINTED = Scalar(45,50,50);
Scalar UPPER_PRINTED = Scalar(75,255,255);

Scalar LOWER_SEAM = Scalar(105,50,50);
Scalar UPPER_SEAM = Scalar(135,255,255);
```

Pattern length

Adjustment of the length of the pattern line can be necessary when using self-designed patterns. This variable based on the measured length when printed out. This variable is relevant for the calculation of the distance consistency, as introduced in 4.4.2 "Distance Consistency", to determine the ratio of millimeters to pixels of each individual photo.

```
double PATTERN_LENGTH_MM = 250;
```

Overlapping tolerance

The overlapping threshold is defined as the distance in pixels within which points are still considered as overlapping when computing the replication accuracy. In theory, overlapping points share a common distance of 0. However, we recognize that hand-sewn seams do not require absolute computational precision. The adjustable overlapping threshold tolerance therefore provides an opportunity for a balanced and realistic measure for the computation of the replication accuracy.

Our program currently considers a pixel from the seam overlapping with the printed line if the distance between them is less than 8 pixels. Considering a pixel resolution of 12.19 megapixels of the photos tested in our application, the chosen threshold is neither excessively high nor insignificant.

```
int OVERLAPPING_THRESHOLD = 8;
```

5.3 Implementation Structure

The essential operations of our assessment are called in the main function of the `Wrapper.mm` file and clasp the following tasks in the same order.

1. Color detection to extract seam and printed line
2. Match seam onto the printed line by coarse registration algorithm
3. Generate output image with coordinates of matched seam
4. Computation of distance consistency and replication accuracy

Matching process in pseudocode

The following algorithm presented in pseudocode displays the search for the alignment by brute-forcing the predefined range within the array of the printed line. After each tested alignment the Chamfer distance is computed to compare the result with the current minimum distance. Later on, the array consisting of the coordinates of the resulting position is passed on to generate the digital output image.

5.4 Sufficient Conditions for the User

To ensure optimal functioning of the application, both on the provider's as well as the user's end, there are some sufficient requirements elaborated in the following.

Algorithm 1 Matching algorithm

while $i \leq rangeEnd$ **do**
  $movedSeam \leftarrow moveSeam(curSeam, pivotA, seam[i])$
  $curDist \leftarrow calculateChamferDist(line, movedSeam)$
  if $curDist \leq minDist$ **then**
    $matchedSeam \leftarrow movedSeam$
    $minDist \leftarrow curDist$
  end if
  $i \leftarrow i + 1$
end while

Advice on the correct usage of indicated colors

As our implementation applies color detection to determine as well as identify the seam and the printed line, the user is obliged to print out the pattern in color as well as to sew with a thread of the indicated color. Further, no similar color shades to these two color shades should be visible in the image taken by the user.

Photo conventions

For the correct detection of lines, the uploaded photo should be taken in an upright format.

5.5 Limitations

Pattern constraints due to matching algorithm

To ensure a seamless usage of our implementation in the following we address some critical limitations of our application. Our application evaluates parallel sewing by overlapping respective components for a high matching of the given line and seam. Consequently, our approach is not suited to assess patterns that are not directly replicated when sewn alongside, such as spiral patterns. Moreover, the current algorithm for matching the seam onto the printed line is based on aligning every leftmost pixel of the lines found in each row, as explained in 4.3.4 "Reducing Array Sizes". This approach means that patterns, where multiple seam lines intersect or run horizontally through a single row, cannot be accurately assessed by our system.

Chapter 6

Results and Discussion

For the evaluation, we examine the results produced by our application for various sample patterns with sewn-on seams and analyze these outcomes in relation to our intended goals. We present the resulting images as well as the analytical metrics computed by our implementation, to provide a comprehensive review of both the visual and qualitative aspects of the performance of our system.

6.1 Evaluated Matching Results

In this section we provide exemplary input photos of the sewing task and the results our implementation yields.

Execution Time For the most part, we identify a very quick computation of results, usually around 1 second. However, we notice differences in the time of execution for two images of the same lines. Figure 6.1 shows both the input images on the left, whereas the image at the bottom is a minimally cropped version of the original image at the top. The resulting alignments on the right however differ by a slightly more accurate matching yielded by the cropped version, which is visible at the lowest part of the aligned lines. Despite the more accurate result however,

Computation time mostly around 1 second

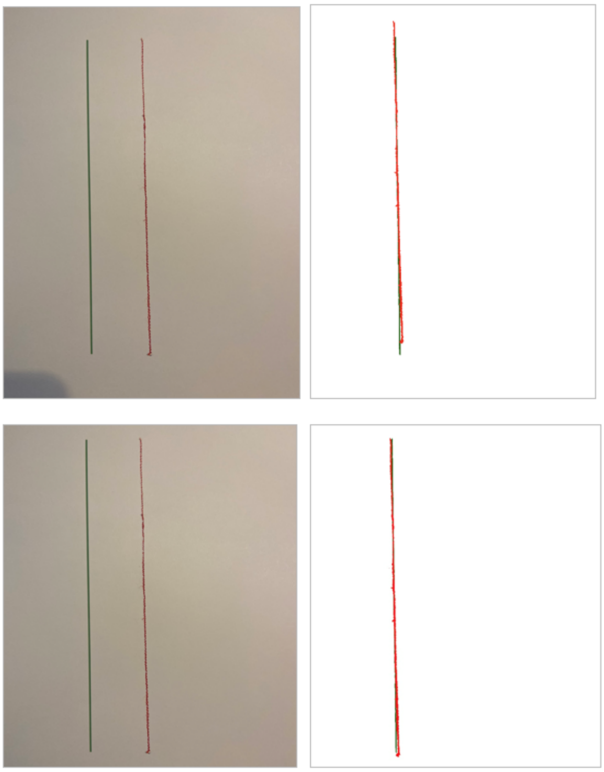

Figure 6.1: Comparison of resulting alignments based on the same photographed lines with a slightly zoomed-in picture at the bottom.

the computation of the alignment using the cropped image took a significant longer time of 26.07 seconds while the original image only took 0.76 seconds.

Accurate alignments

Overall Results During the assessment phase of our application, conducted with various images of different patterns and seams, we extracted the following insights regarding its performance. The matching process yields promising results by effectively aligning the seam onto the printed line, which can be observed in the output images respectively. The distance consistency, which is dependent on the resulting alignment, likewise produces a realistic outcome. However, while the replication accuracy approximates the similarity between both lines, in certain examples it yields slightly off results, not aligning with initial expec-

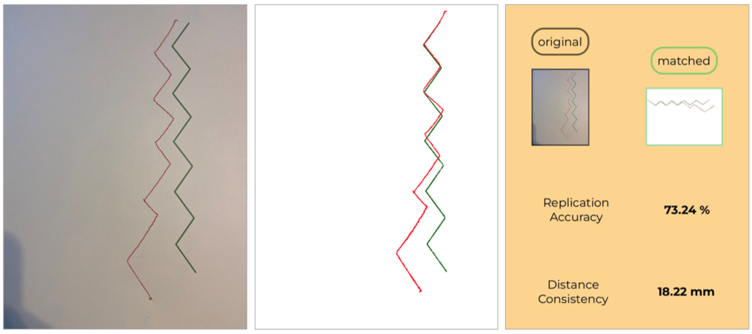

Figure 6.2: Results of aligned zigzag lines, yielding a replication accuracy of 73.24 % and a distance consistency of 18.22 mm.

tations.

Slightly imbalanced replication accuracy

Such an example is given in Figure 6.2, which displays the input and the results evaluated by our implementation. On the left, the original image showcases a zigzag pattern with the given zigzag line printed in green and the red seam sewed next to it. The center image reveals the result of the matched lines and the image on the right presents the evaluation view provided to the user. This evaluation view includes the calculated metrics with a replication accuracy of 73.24 % and a distance consistency of 18.22 mm computed in 1.81 seconds.

Higher replication accuracy than expected despite plausible matching

The image also demonstrates how the alignment, achieved through coarse registration, effectively matches the upper half of the zigzag seam to the printed line. As one observes the seam progressing toward the bottom, the distance between the seam and the printed line visibly increases, a discrepancy that is also visible in the resulting image. However, the yielded replication accuracy seems to be higher than one would expect, which does not entirely coincide with an estimation of no more than 50 % by observing the produced output image.

In another example shown in Figure 6.3, the yielded replication accuracy yields a far more unbalanced result despite an overall well sewn regular seam, as can be examined in the input image on the left. The matched lines in the center reflect few single overlapping points, resulting in a fi-

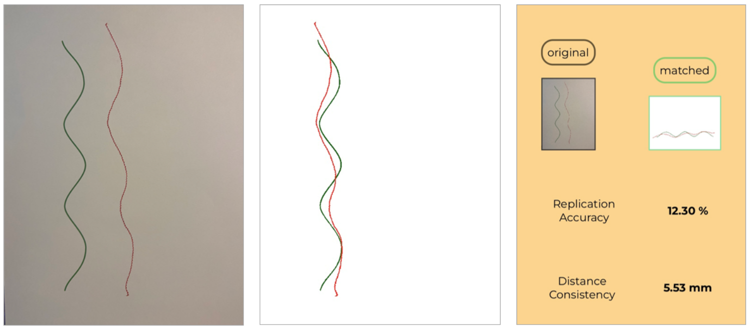

Figure 6.3: Results of aligned wavy lines with a final replication accuracy of 12.30 % and distance consistency of 5.53 mm.

nal outcome of 12.30 % accuracy computed in 1.47 seconds. Reasons could lie in the strictly defined computation of the replication accuracy, which only takes into account overlapping points within a small pixel range. Therefore, while some pixels overlap, the remaining pixels of the seam are not taken into account for the result despite their overall closeness to the printed line.

Results for Highly Accurate Sewing An overall well sewed example of a straight line with its computed evaluation is depicted in Figure 6.4. The distance consistency yields a possibly accurate result of 1.20 mm. The replication accuracy however only returns 76.67 % despite a high visual matching. This could be due to several red points of the determined seam at the upper and lower ends not exactly overlapping with the green printed line, which can be examined in the middle image in Figure 6.4.

For comparison, we tested our application on an image with two printed straight lines, as can be observed in Figure 6.5. Here, the assessment returns an accurate application accuracy of 100 % and a distance consistency of 0.78 mm, which matches the output image in the center. This result supports our assumption of a very strictly classified computation of overlapping points.

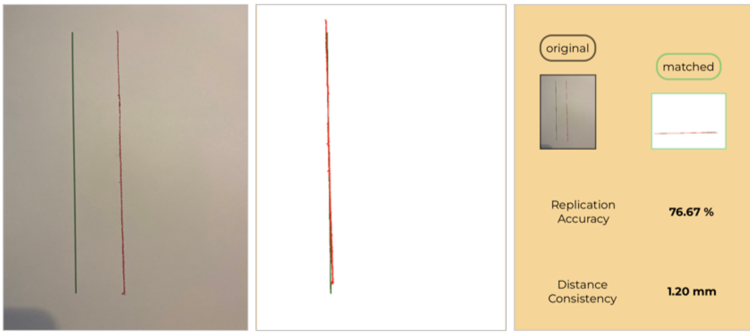

Figure 6.4: Example of a well sewn parallel seam with realistic distance consistency of 1.20 mm but comparable low replication accuracy.

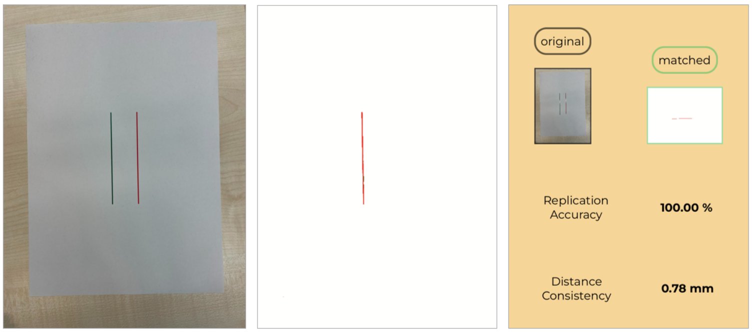

Figure 6.5: Tested printed lines in red and green with completely overlapping lines as final alignment and a replication accuracy of 100 %.

6.2 Discussion

In conclusion, we summarize the results of our implementation as follows. Concerning the alignment of the seam and the printed line, the visual representations testify an accurate matching for all tested patterns. However, the replication accuracy does not reliably reflect an adequate value for every alignment. The overlapping points give a pixel-accurate depiction of the yielded overlapping. Such strict division in the context of a practical sewing task may not be necessary nor suitable. In contrast, the distance consistency offers a well representation of the demanded task of sewing in parallel. Considering our results, we attribute higher significance to the distance consistency values when evaluating sewing skills with our system as this value also coincides with our intended task of tracking parallel sewing.

Distance metric as a possible third objective to evaluate the result

As the replication accuracy only computes the percentage of matching points on the guiding line, it does not give more information on how much the non-matching points of the seam deviate from the given line. Therefore, this metric does not present the resulting task well enough and we suggest the evaluation of using an additional variable that focuses on the shape dissimilarities in a broader manner, e.g. by evaluating the distance between remaining points of the seam that do not overlap with the printed line.

Promising matching results and further optimizations

To summarize, we were able to comply our research question on finding ways to directly assess practical sewing skills by proposing a promising application concerning the issue. Our system evaluates sewing skills by focusing on the user's ability to sew along a given line in a consistent distant. With color detection, we are able to effectively recognize seams and printed lines in an image uploaded by the user. The resulting matching gives us indications on the accuracy of the seams. However, optimizations may enhance the rating of the sewing skills by adding further result values for a precise evaluation.

Chapter 7

Summary and Future work

The main goal of this thesis was to design an automatic assessment to classify users' sewing skills. Following this, we implemented an application that uses color detection for the recognition of lines and coarse registration to compare their similarity. The results of our implementation were presented in the previous chapter 6 "Results and Discussion". In the following, we give a summary and discussion of our findings and indicate how future work can extend them.

7.1 Summary and Contributions

Application workflow

Our research continues on previous work designing an automatic DIY assessment. We concentrated on the handcrafting of sewing and chose to evaluate the task of sewing with a seam allowance. The overall concept of the skill assessment prototype aims to classify each user's current level of expertise in sewing to eventually recommend skill-based tutorials. To realize our idea of an automated evaluation of practical sewing skills we ask users to print out our designed pattern. Their task is to sew on the paper along the printed line with an indicated distance. Then, by sending a photo of the sewn-on sheet to our application, our system analyzes the result and gives back values considering the shape of the seam and the distance to the guideline.

Implementation approach

By investigating different computer vision techniques we evaluated color detection to be most suitable for the determination of precise printed lines and seams. Initial approaches involving concrete object detection turned out to be not precise enough for the shape comparison of delicate lines. Further, we developed methods to evaluate the properties of the shape of the stitched seam regarding our task. By adapting the principle of coarse registration, we matched the seam onto the printed line to determine their level of similarity. As a result, we are able to return feedback variables that reflect the user's ability to sew parallel to a given line in a continuous distance as well as an overall rating of how well they performed in replicating the line. Additionally, a visual representation of the aligned lines gives graphical insight into the computed result.

Evaluation of results

With our implementation, we contribute to the original intended goal of providing sewing recommendations suited to each user based on their current skills. Our assessment of tracking the seam allowance as one aspect of evaluating a sewed product does not give a rating of someone's overall sewing expertise. As feedback, we therefore decided to return only the computed analysis variables without further classification. Ultimately, while the computed overlapping points for the replication accuracy do not always precisely reflect the result, our system is able to return an accurate matching of seam and printed line and indicate how consistent the distance was kept. Our approach is therefore directly applicable and offers promising results to build on.

Classification into the field of Human-computer interaction

The goal of our thesis comprises the automated skill assessment for hobby sewers. Following this, our research primarily concentrates on exploring ways of simple yet effective skill evaluation with limited tools and prerequisites from the users. We use software systems to enable an automatic objective process evaluating practical skills. We therefore enhance the software-unrelated fabrication with a computer-aided system, connecting automation and conventional handcraft. Future work may explore further ways of integrating soft- and hardware into traditional practices for more efficient and faster operation regarding tools and tutorial selection and procedures suited for automation.

7.2 Future Work

In this work, we explored methods for a system to automatically assess sewing skills directly. Our approach yields promising results and opens opportunities for further explorations and modifications. These could be built upon our current work by enhancing it, discovering new methodologies for the assessment of sewing skills or adapting our approach onto other disciplines. This section provides a short outlook on future work and what issues still need addressing.

Propose future works comprise software enhancements, the practical evaluation and further explorations in assessing practical skills

Our system is able to accurately align both lines in the sewing task. However, we recognize potential improvements, in particular in the evaluation metrics. One such modification could involve the enhancement of the application accuracy. Also, additional metric could be introduced to evaluate the distance between both aligned lines, contributing to an overall skill score. Such a metric would provide a more comprehensive assessment of sewing proficiency, taking into account not only the alignment accuracy but also degree of difference from the seam to the guiding line. This could offer a more balanced and detailed evaluation of an individual's sewing skills.

Adjusted evaluating values and further patterns

A possible next step involves the conduction of a user study to assess and refine the quality of the application.

User study

Future work can also look into realizing further automated sewing skill assessments. These include the theoretical skill evaluation and the integration of those for the following recommendation of tutorials based on the user's current skills, as suggested in Rahm [2022].

Further sewing skill evaluation

Our proposed methods could also be adapted for the assessment various further disciplines of handcraft. This

Assessment of practical skills in other handcrafts could include the development of simplified methods by using image recognition technology to evaluate properties of a handcrafted product for a quick adaptation as an alternative to more complex machine learning approaches.

Bibliography

Stavros Asimakopoulos, Grigorios Asimakopoulos, and Frank Spillers. Motivation and user engagement in fitness tracking: Heuristics for mobile healthcare wearables. *Informatics*, 4(1), 2017. ISSN 2227-9709. doi: 10.3390/informatics4010005. URL `https://www.mdpi.com/2227-9709/4/1/5`.

Claus Bahlmann, Gunther Heidemann, and Helge Ritter. Artificial neural networks for automated quality control of textile seams. *Pattern Recognition*, 32(6):1049–1060, 1999. ISSN 0031-3203. doi: https://doi.org/10.1016/S0031-3203(98)00128-9. URL `https://www.sciencedirect.com/science/article/pii/S0031320398001289`.

H. G. Barrow, J. M. Tenenbaum, R. C. Bolles, and H. C. Wolf. Parametric correspondence and chamfer matching: Two new techniques for image matching. In *Proceedings of the 5th International Joint Conference on Artificial Intelligence - Volume 2*, IJCAI'77, page 659–663, San Francisco, CA, USA, 1977. Morgan Kaufmann Publishers Inc.

Federico Bolelli, Stefano Allegretti, Lorenzo Baraldi, and Costantino Grana. Spaghetti labeling: Directed acyclic graphs for block-based connected components labeling. *IEEE Transactions on Image Processing*, 29:1999–2012, 2020. doi: 10.1109/TIP.2019.2946979.

Tadhg Brosnan and Da-Wen Sun. Inspection and grading of agricultural and food products by computer vision systems—a review. *Computers and Electronics in Agriculture*, 36(2):193–213, 2002. ISSN 0168-1699. doi: https://doi.org/10.1016/S0168-1699(02)

00101-1. URL https://www.sciencedirect.com/science/article/pii/S0168169902001011.

Chi-Ho Chan and G.K.H. Pang. Fabric defect detection by fourier analysis. *IEEE Transactions on Industry Applications*, 36(5):1267–1276, 2000. doi: 10.1109/28.871274.

Yago Díez, Ferran Roure, Xavier Lladó, and Joaquim Salvi. A qualitative review on 3d coarse registration methods. *ACM Comput. Surv.*, 47(3), feb 2015. ISSN 0360-0300. doi: 10.1145/2692160. URL https://doi.org/10.1145/2692160.

Hazel Doughty, Dima Damen, and Walterio Mayol-Cuevas. Who's better? who's best? pairwise deep ranking for skill determination. pages 6057–6066, 06 2018. doi: 10.1109/CVPR.2018.00634. URL https://ieeexplore.ieee.org/document/8578732.

Georgia Giblin, Elaine Tor, and Lucy Parrington. The impact of technology on elite sports performance. *Sensoria: A Journal of Mind, Brain Culture*, 12, 11 2016. doi: 10.7790/sa.v12i2.436.

Jun Gong, Fraser Anderson, George Fitzmaurice, and Tovi Grossman. Instrumenting and analyzing fabrication activities, users, and expertise. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI '19, page 1–14, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 9781450359702. doi: 10.1145/3290605.3300554. URL https://doi.org/10.1145/3290605.3300554.

Rafael Grompone von Gioi, Jérémie Jakubowicz, Jean-Michel Morel, and Gregory Randall. LSD: a Line Segment Detector. *Image Processing On Line*, 2:35–55, 2012. https://doi.org/10.5201/ipol.2012.gjmr-lsd.

Paul VC Hough. Method and means for recognizing complex patterns, December 18 1962. US Patent 3,069,654.

Stacey Kuznetsov and Eric Paulos. Rise of the expert amateur: Diy projects, communities, and cultures. In *Proceedings of the 6th Nordic Conference on Human-Computer Interaction: Extending Boundaries*, NordiCHI '10, page

295–304, New York, NY, USA, 2010. Association for Computing Machinery. ISBN 9781605589343. doi: 10.1145/1868914.1868950. URL `https://doi.org/10.1145/1868914.1868950`.

Cassim Ladha, Nils Y. Hammerla, Patrick Olivier, and Thomas Plötz. Climbax: Skill assessment for climbing enthusiasts. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp '13, page 235–244, New York, NY, USA, 2013. Association for Computing Machinery. ISBN 9781450317702. doi: 10.1145/2493432.2493492. URL `https://doi.org/10.1145/2493432.2493492`.

Lo Lee and Melissa G. Ocepek. From virtual to physical: An exploratory study on how online social networks and communities influence decision-making in everyday crafting. pages 2232 – 2241. Proceedings of the 56th Hawaii International Conference on System Sciences, 2023. URL `https://hdl.handle.net/10125/102907`.

Marc Levin, Tyler McKechnie, Shuja Khalid, Teodor P. Grantcharov, and Mitchell Goldenberg. Automated methods of technical skill assessment in surgery: A systematic review. *Journal of Surgical Education*, 76(6):1629–1639, 2019. ISSN 1931-7204. doi: https://doi.org/10.1016/j.jsurg.2019.06.011. URL `https://www.sciencedirect.com/science/article/pii/S1931720419301643`.

Addie Martindale and Ellen McKinney. Why do they sew? women's motivations to sew clothing for themselves. *Clothing and Textiles Research Journal*, 38(1):32–48, 2020. doi: 10.1177/0887302X19872552. URL `https://doi.org/10.1177/0887302X19872552`.

Huber Burda Media. Burda style, 2021. URL `https://www.burda.com/de/marken/burda-style/`.

Catarina Mota. The rise of personal fabrication. In *Proceedings of the 8th ACM Conference on Creativity and Cognition*, C&C '11, page 279–288, New York, NY, USA, 2011. Association for Computing Machinery. ISBN 9781450308205. doi: 10.1145/2069618.2069665. URL `https://doi.org/10.1145/2069618.2069665`.

Henry Y.T. Ngan, Grantham K.H. Pang, S.P. Yung, and Michael K. Ng. Wavelet based methods on patterned fabric defect detection. *Pattern Recognition*, 38(4):559–576, 2005. ISSN 0031-3203. doi: https://doi.org/10.1016/j.patcog.2004.07.009. URL `https://www.sciencedirect.com/science/article/pii/S0031320304003693`.

Ricarda Rahm. Automating user skill evaluation to provide matching diy tutorials. Master's thesis, RWTH Aachen University, Aachen, July 2022.

Reddit. r/sewing. URL `https://www.reddit.com/r/sewing/`.

P. Smith. Global revenue of the apparel market 2014-2027, September 2023. URL `https://www.statista.com/forecasts/821415/value-of-the-global-apparel-market`.

Satoshi Suzuki and KeiichiA be. Topological structural analysis of digitized binary images by border following. *Computer Vision, Graphics, and Image Processing*, 30(1):32–46, 1985. ISSN 0734-189X. doi: https://doi.org/10.1016/0734-189X(85)90016-7. URL `https://www.sciencedirect.com/science/article/pii/0734189X85900167`.

Eric von Hippel. *Democratizing Innovation. DEMOCRATIZING INNOVATION.* MIT Press, CA, April 2005.

Marco Wolf and Shaun Mcquitty. Understanding the do-it-yourself consumer: Diy motivations and outcomes. *AMS Review*, 1, 12 2011. doi: 10.1007/s13162-011-0021-2.

Index

Typeset December 6, 2023