Concept for a Simulation-based Approach Towards Automated Handling of Deformable Objects – A Bin Picking Scenario

Markus Wnuk*, Andreas Pott*, Weilang Xu†, Armin Lechler* and Alexander Verl*
*Institute for Control Engineering of Machine Tools and Manufacturing Units,
University of Stuttgart, Seidenstr. 36, Stuttgart, Germany
†Department of Mechanical Engineering, The University of Auckland, 20 Symonds St., Auckland 1001, New Zealand
(Corresponding author: M. Wnuk, e-mail: markus.wnuk@isw.uni-stuttgart.de)

Abstract—**Handling of deformable objects with industrial robots holds many unresolved challenges. Especially, describing and predicting the deformed state is computationally expensive and therefore difficult under the requirements of manufacturing environments. A concept for a simulation-based approach towards bin picking of deformable objects, is presented in this paper. The emphasis of the approach lies on the subtask of localisation and pose estimation, but regards the context of gripping and manipulation as well. A multi-body modelling approach is considered to model the deformation of soft objects. The basic idea is to provide a reduced order model accounting for the requirements of short computation times. At last, the implementation of the proposed bin picking system is discussed and further research activities with the presented system are outlined.**

I. INTRODUCTION

The interaction between rigid robotic devices and soft materials like human tissues, work pieces made of rubber, or textiles gives rise to numerous challenges due to the complex material behaviour.

To take on these challenges an International Research Training Group (IRTG) between the University of Auckland and the University of Stuttgart has been established recently. This joint research program named "Soft Tissue Robotics" pursues to push the boundaries of current robot technology by the means of an interdisciplinary approach incorporating the fields of simulation technologies, cyber-physical engineering approaches, robotic device technology, and biomedical engineering.

In contrast to rigid bodies, the state of a deformable object is not defined by 6 degrees of freedom (DOF), but literally an infinite number of DOFs. They describe the current shape of the deformable objects under the given constraints . Hence, in comparison to the manipulation of a rigid object, the shape of a deformable object is neither exactly known nor constant. This exacerbates the automated localisation and handling significantly [1]. Whereas rigid objects are localised by incorporating commonly available CAD data models and matching them with the acquired image data [2], an appropriate data model capturing the manifold appearances of a deformable object has to be found primarily.

Despite these challenges, automated processing of deformable objects such as seals, hoses, ropes, wires, textiles or cloths is highly desirable from the manufacturing point of view [3]. Especially, handling tasks are of particular interest since about 55% of the applications which involve industrial robots include object handling [4]. Specific manual handling examples, showing potential to be automated with robots, are wiring of switch cabinets which takes up to 50% of the total building time [5], and mounting of wire harnesses in the automotive industry where a higher degree of automation is long desired [6].

II. STATE OF THE ART FOR BIN PICKING DEFORMABLE OBJECTS

A popular task in the development of robotic automation, comprising relevant requirements related to automation of object handling, is bin picking [7]. It allows for facing the arising challenges in a well-defined environment. Thus, a bin picking scenario is considered as ideal use case where the interaction between rigid robotic devices and soft objects can be observed within a variety of tasks, such as localisation, finding appropriate gripping positions and applying control or manipulation strategies.

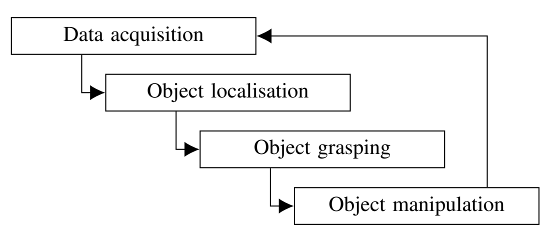

Figure 1. Process of bin picking derived from [8]. Starting with the data acquisition the process is followed by the object localisation and object grasping. After grasping and performing a predefined manipulation task the process is finished and starts anew with another object from the bin.

In the following, a short overview of relevant literature related to bin picking soft objects is provided. Existing approaches and successfully implemented solutions are discussed. Since the bin picking problem is mainly investigated for rigid objects, the review refers primarily towards bin picking approaches concerning rigid objects in Subsection II-A and inquires the soft material modelling perspective in Subsection II-B.

A. Bin picking

The task of bin picking can be divided in several subtasks. These tasks are data acquisition, object localisation, grasp point identification and transport to a target position for manipulation. Among them, the localisation is considered most challenging according to [8] and for this reason it will be the main focus of our research.

Reliable localisation of rigid objects is usually based on 2D intensity or 3D distance images [9]. A successful implementation allowing the localisation of piston rods, using 3D depth data, is accomplished in [2]. For the pose estimation a random sample matching (RANSAM) approach which is based on the random sampling consensus algorithm (RANSAC) [10] is used. Another solution is presented by Palzkill [11], who uses construction heuristics in combination with a Generalised Hough Transformation for the object pose detection. In [12] non-uniform objects are localised by approximating the obtained point cloud data with cylinders, proving that localisation of objects with unknown shapes is feasible as long as they can be approximated by geometric primitives.

In contrast to localisation of rigid objects, little research has focused on the localisation and estimation of the pose of deformable objects. Nevertheless, some approaches for localisation of deformable objects have been presented. For example a neural network based approach where the recognition is based on a classification with self-organizing maps (SOM) is presented in [13]. A drawback of this approach is the need for texture or colour properties which are not always available. In [14] a towel folding robot, detecting grasping points by using depth discontinuities of acquired stereo image data, is introduced. However, this approach is restricted to 2D planar geometries.

It can be concluded that a major issue evading the applicability of matching algorithms, is the uncertainty about the shapes of a deformable object, resulting from the infinite number of DOFs. We conjecture to enable localisation and pose estimation of deformable objects by abstracting the objects within an appropriate modelling approach. The model should capture only the essential characteristics of the deformation behaviour and therefore reduce the DOFs to a manageable amount. Coupling this model of largely reduced order with simulation technology provides an appropriate data model which includes the relevant information about potential shapes for the matching algorithm. Thus, finding an appropriate modelling approach is key to apply existing matching algorithms for the localisation of deformable objects.

B. Material modelling of soft tissues

Soft tissues such as muscle tissue or organs have certain analogies to technical work pieces built from rubber, polymers, or fibre-reinforced composites. This analogy is expressed within the underlying constitutive models ranging from linear elastic models, over non-linear elastic models (hyperelasticity), to time-dependent viscoelastic, or plastic models [15]–[17]. Therefore, the modelling approaches for soft tissues coming from the field of biomechanics and biomedical research are a valuable endorsement for the simulation-based approach within the proposed bin picking scenario, which originates rather from industrial manufacturing. Hence, common modelling approaches governed by a biomedical perspective are discussed in the following.

The equations of motion of a soft material are described by partial differential equations (PDE) [18]. These can be derived from continuum mechanics with the aid of the Lagrange's equations of the second kind while respecting the constitutive behaviour of the material. Since PDEs are commonly not solvable analytically they are usually discretised in space with the well-known Finite Elements Method (FEM) [19]–[21] or the Finite Differences Method (FDM) [18], [22]. The resulting set of coupled ordinary differential equations (ODE) is then integrated numerically.

The FEM method is widely spread in the medical field where accurate models, capturing the detailed behaviour of soft tissues including large deformations, are desired [15]. Thus, much research has been done in improving the accuracy and lowering the computation times of soft material FEM models [20], [21], [23], [24]. Despite many efforts in reducing the computational cost of the FEM models, the computation times remain a major drawback of this modelling approach [25].

A method developed to account for fast computation times, as an alternative to FEM, is mass-spring systems (MSS). MSS consist of a network of point masses connected by spring and damper elements, representing the deformable body. The stiffness and damping coefficients of the interconnections are determined in a way that the model mimics the soft tissue's deformation behaviour [26]. Due to the fast computation times, this method is frequently used in computer graphics and game physics [22] as well as in surgical applications [27]. A major disadvantage of the MSS approach is, that it is not based on a constitutive material model and therefore, there is no guarantee that deformation behaviour of the deformable object is correctly modelled [27]. Especially, capturing large deformations of multiphase materials is problematic in terms of determining appropriate model parameters and model topologies [24], [28].

Another approach, coming from classical mechanics, is multi-body systems (MBS). MBS are closely related to MSS and frequently used in biodynamic modelling. They consist of rigid bodies coupled by spring and damper elements and are used to model systems undergoing large deformations [29]. An ongoing development of MBS is the extension towards flexible multi-body systems (FMBS) by the integration of flexible structures in the MBS. A common MBS approach for modelling deformable objects or structures, is the finite segment method. It is widely used to capture the motion of cables [30], or the flexible behaviour of human bodies in crash test simulation scenarios [31]. The deformable object is described with a set of rigid bodies interconnected by joints with a certain number of DOF, parametrised with appropriate stiffness and damping coefficients [32]. This allows capturing large displacements and deformations with low computational costs. Major drawbacks of the rigid segment approach are the identification of appropriate joint parameters and the selection of the number, size, and location of the rigid segments [33].

Among FEM, MSS, and MBS many alternative approaches beyond the scope of this paper exist for the modelling of soft materials. It is concluded, that a trade-off between accuracy and computational costs has to be found, satisfying the requirements of a bin picking scenario. Since each of the modelling approaches exhibits individual strength and shortcomings, a model-based approach is always subjected to certain limitations. Therefore, it is crucial to choose a modelling approach matching the specific requirements of a bin picking scenario. A classification of deformable objects, categorizing types with similar characteristics, enables us to derive requirements for the object model and helps to evaluate the applicability of a chosen modelling approach. Thus, the selection of a modelling approach as well as a classification of deformable objects is discussed in the following.

III. Concept for simulation based handling of deformable objects

The objective of our approach is to investigate research questions concerning the automated handling of deformable objects within the framework of a bin picking scenario. This implies specific requirements for the subtasks of localisation and manipulation, since in contrast to bin picking of rigid objects, the shape of the deformable object is not explicitly defined. The missing information about the deformed state is supposed to be provided by a multi-body modelling approach, capturing the gross deformation behaviour of the soft material. This modelling approach is described in Subsection III-A. Since a generic solution for bin picking does not even exist for rigid objects, a general solution for bin picking arbitrary deformable objects is not anticipated to be found straight away. Thus, restraining our approach to certain classification criteria is discussed in Subsection III-B. In Subsection III-C, the overall system setup is envisaged, which will serve as framework for future research.

A. Approach for modelling and simulation

As described in Section II, the implemented localisation algorithms for bin picking of rigid objects rely on a given data model in form of CAD data or geometric primitives. These data models are matched with acquired sensor data for the estimation of pose and orientation. In case of deformable materials, these kinds of data models are merely available for a reference configuration, but by no means for the deformed state. This leads to the question, how the deformed state can be described and how visual data and image processing techniques can be employed to estimate the deformation.

We propose a simulation-based approach incorporating an appropriate object model to provide the necessary information about deformed object. From the perspective of localisation,

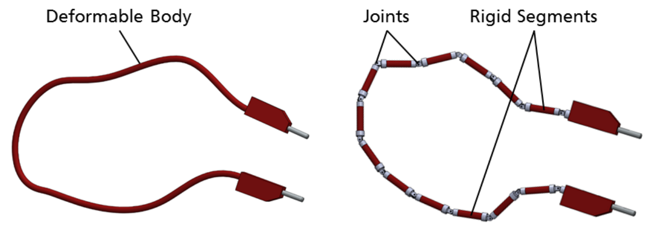

Figure 2. Basic idea of the segmentation of deformable objects into rigid segments to capture the gross deformation behaviour. A deformed geometry (left) as well as a multi-body model (right) of a banana plug is depicted. The deformation behaviour of the wire is modelled coarsely with multiple joints between the rigid segments. The computational costs are rising with the number of joints.

two major requirements concerning the simulation can be derived. At first, the model should capture the large deformation behaviour, since small deformations of the objects can be compensated within adjustments of the matching algorithm by using an approach as [12]. Hence, capturing the large deformations is key for successful matching. Secondly, the model must not require too much computational power because a vast amount of possible object configurations have to be computed and compared with the acquired sensor data within minimal time, satisfying the demand of low cycle times, for instance in a serial production scenario.

The FEM and MSS models presented in Subsection II-B do not meet these requirements obviously. The FEM approach is subjected to high computational costs while the MSS models satisfy the computation time requirement, but do not capture large deformation. Therefore, a multi-body modelling approach is considered to capture the crucial characteristics of the deformation behaviour of a deformable object. An illustration of the basic idea is given in Fig. 2. This approach provides a model of a largely reduced order compared to a finite element model. Thus, it allows meeting the requirements of low computation times.

To overcome the major drawback of the identification of appropriate joint parameters as described in Subsection II-B, a parameter learning approach in the manner of [25] can be employed. The idea is to utilise acquired sensor data, such as force feedback and visual data, to obtain reasonable model parametrisation. Further challenges are the derivation of an appropriate topology of the MBS to characterise the deformation appropriately, and the reconstruction of the outer appearance once the structural deformation is known. Approaches from the field of computer graphics allowing the skeletisation of 3D geometries as presented by [34] and [35] may help to resolve these problems.

Due to the huge variety of soft material properties and geometries, the proposed MBS approach is constrained only to specific application scenarios. To account for the application of bin picking, a classification regarding the different subtasks according to Fig. 1 is given in the following.

B. Classification of deformable objects with respect to bin picking

A first approach towards a classification of deformable objects is given in [36]. They define five classes of objects with respect to a manipulation task, under the assumption of isotropic material. The applied force and the resulting deformation are used as measures and matched with the material properties of elastic and plastic deformation. This leads to a classification describing the feasibility of the manipulation task from simple (no deformation) to complex (high plastic deformation). The approach comprises a classification according to the material properties implicitly, where a soft material is characterised by its underlying constitutive model.

In [37] a classification based on the shape geometry of flexible materials is given. Deformable objects are divided in linear (e.g. cable, wire), sheet-like (e.g. fabric, garment) and three dimensional (e.g. soft tissue, meat) entities. Afterwards these classes of flexible materials are related to specific industrial manipulation tasks covering the perspective of automated handling.

However, the given classifications are not sufficient with respect to a simulation-based approach towards bin picking, since they focus mainly on the aspects of manipulation and handling. From the perspective of our approach it is necessary to consider criteria from the tasks of localisation and modelling as well.

In terms of localisation, the subtasks of data acquisition, image processing, and matching pose additional requirements towards a classification. For the data acquisition, the surface of the deformable object is a major concern. Characteristics such as reflectance influence the availability and quality of acquired sensor data. For the subsequent image processing, features such as textures or patterns facilitate the object identification and the pose estimation, since they constrain the search tree of possible object configurations. To match the acquired sensor data with a computational model, it is required to differentiate between determined and arbitrary geometries of deformable objects. A determined geometry excels by the availability of a reference geometry as for example industrial manufactured parts, e.g. hoses with defined diameter and length. Whereas no such reference exists for objects with arbitrary geometries, e.g. natural products such as fruits with varying size. Hence, the availability of additional information induced by a reference geometry has to be considered within a classification as well.

Concerning the proposed MBS modelling approach, as described in Subsection III-A, a classification has to respect the topology of the object. Considerations about the spatial arrangement and symmetries of the model allow to simplify the real world scenario by modelling linear, plane or spatial topologies with corresponding DOFs in one, two or three dimensions, and therefore are a measure for the complexity of the modelling approach.

A classification with respect to bin picking, based upon the introduced preliminary studies by [36] and [37], requires additional criteria to classify deformable objects. It has to account

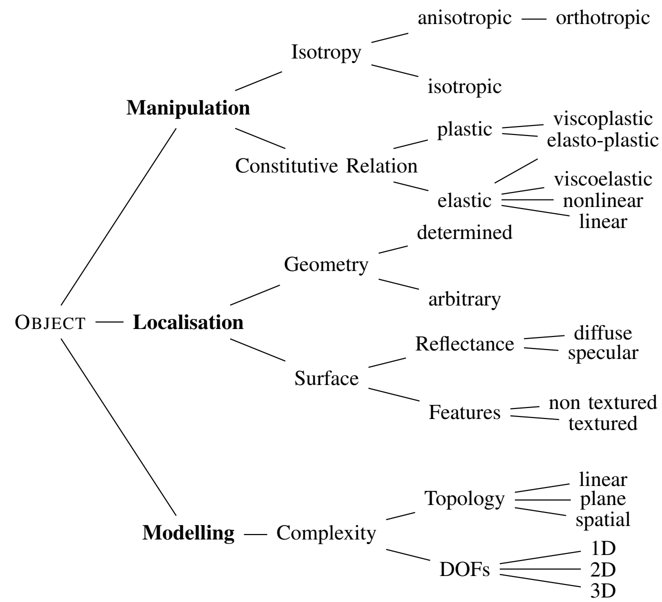

Figure 3. Classification of deformable objects according to important characteristics with respect to a simulation-based approach towards bin picking

for the different perspectives of a bin picking scenario form manipulation over localisation to modelling. A classification scheme for our simulation-based approach is given in Fig. 3.

C. Concept for a simulation-based bin picking system

Based upon the previously discussed classification criteria, we are able to derive requirements for the development of a bin picking system coping with deformable objects.

The physical system setup is derived from common robot cells used for bin picking applications as described in [38], [39]. The soft objects, as work pieces, are supplied in a bin, which could be sorted properly or placed chaotically. It should be noticed that the difficulty of the bin picking task scales with the derangement of the work pieces. In our research, we intend to achieve localisation and gripping of disordered work piece arrangements since this is the most application related situation [11]. Visual sensor data are acquired via an appropriate camera system. The objective of the bin picking system is to manipulate the deformable objects in a defined way. Therefore, a variable setup consisting of a storage place and an assistive device is considered. In this context, the storage place is equivalent to a device representing a manipulation objective as for example a hole for a peg-in-hole task or a hole fixture [1], [40]. The purpose of the assistive device is to provide assistance for the manipulation task because it is often difficult or impossible to handle deformable objects gripping only on one position over their entire geometry. The design of the assistive device is dedicated to a certain manipulation task. It can be a fixture or a kinematic with various degrees of freedom respectively a second robotic device [41].

The core of the system consists of a commercially available robot with a serial kinematic of at least 6 DOFs, a robot control and a software framework for the control of the

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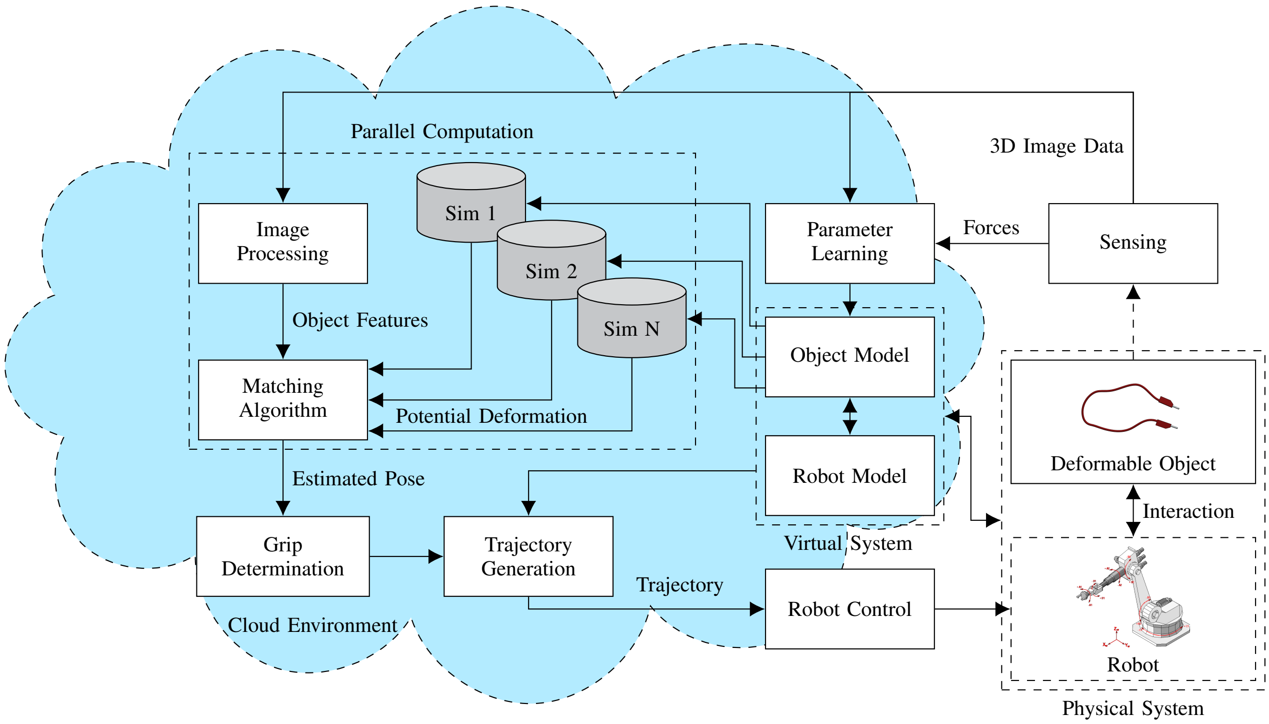

Figure 4. Overview of the proposed concept for handling deformable objects with a robot within a bin picking scenario.

bin picking task. The concept of the software framework is depicted in Fig. 4. 3D image data are acquired for the purpose of localisation referring to successfully implemented bin picking applications such as [8], [42]. The sensor data are then processed in an image processing unit extracting useful information, such as interesting points or features, for the matching algorithm by using the approach in [11]. Matching the extracted information from the image processing with our modelling approach from Subsection III-A is the subject of our ongoing efforts.

Presuming a reliable matching algorithm, able to supply the deformable object's pose, we can determine appropriate gripping positions and generate an according trajectory. For the trajectory generation the deformation behaviour of the object as well as the kinematic of the robot are considered. The planned trajectory is then fed forward to the robot control, whereby we assume the robot to follow the planned trajectory as long as it operates within its technical specifications.

Returning to the learning strategies, mentioned in Subsection III-A, force feedback along with the visual data of the deformable object and the position feedback of the robot drives are coupled to estimate appropriate parameters for the multi-body model. This enables the system to adapt the model parametrisation depending on the given material characteristics of the handled objects.

To cope with the computationally demanding tasks within the image processing, the model computation, the matching process and the learning algorithms, a parallel computational architecture is considered using state-of-the-art multi-core processes. Especially, the multifold MBS simulation and the matching process are anticipated to be well parallelisable tasks. The computation can either be done locally with the aid of several graphic adapters or in a cloud environment benefiting from the scalability and availability of computational power.

IV. Discussion and Conclusion

A concept of a system setup for a bin picking scenario, pursuing various research questions in the field of the interaction between rigid robots and deformable objects, has been presented. Within this context, we proposed our approach from the manufacturing point of view. The requirements for the system setup are acquired from a literature review regarding successfully implemented bin picking applications for rigid objects and state-of-the-art simulation techniques of soft tissue modelling approaches. For the simulation-based approach a multi-body model, representing a model of largely reduced order to facilitate computation, is proposed. To rate the complexity of bin picking a specific deformable object and evaluate the resulting requirements for the respective bin picking system, a classification scheme was developed. At last, the envisaged framework for the bin picking system is presented. Further efforts will be made to set up the proposed system.

For the purpose of formulating a concrete use case that leads our research towards the fundamental problems of handling soft materials, deformable linear objects such as cables and wires will be the focus of our research. This class of objects is especially suited for the proposed multi-body modelling approach because they premise a desired chain-like structure.

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