Abstract

Estimating the 3D hand pose from a 2D image is a well-studied problem and a requirement for several real-life applications such as virtual reality, augmented reality, and hand-gesture recognition. Currently, good estimations can be computed starting from single RGB images, especially when forcing the system to also consider, through a multi-task learning approach, the hand shape when the pose is determined. However, when addressing the aforementioned real-life tasks, performances can drop considerably depending on the hand representation, thus suggesting that stable descriptions are required to achieve satisfactory results. As a consequence, in this paper we present a keypoint-based end-to-end framework for the 3D hand and pose estimation, and successfully apply it to the hand-gesture recognition task as a study case. Specifically, after a pre-processing step where the images are normalized, the proposed pipeline comprises a multi-task semantic feature extractor generating 2D heatmaps and hand silhouettes from RGB images; a viewpoint encoder predicting hand and camera view parameters; a stable hand estimator producing the 3D hand pose and shape; and a loss function designed to jointly guide all of the components during the learning phase. To assess the proposed framework, tests were performed on a 3D pose and shape estimation benchmark dataset, obtaining state-of-the-art performances. What is more, the devised system was also evaluated on 2 hand-gesture recognition benchmark datasets, where the framework significantly outperforms other keypoint-based approaches; indicating that the presented method is an effective solution able to generate stable 3D estimates for the hand pose and shape.

Keywords: Hand Pose Estimation, Hand Shape Estimation, Deep Learning, Hand-Gesture Recognition

1. Introduction

The 3D pose estimation is a fundamental technology for computer vision based approaches that has gained great importance in the latest years, especially due to the advances in several practical applications such as virtual reality (VR) [1], augmented reality (AR) [2], sign language recognition [3], and, more in general, gesture recognition [4]. In these fields, much of the effort is directed towards the pose estimation of hands since, as a consequence of their high joint number, they are one of the most complex components of the human body [5]. To address this complexity, either a model- or data-driven strategy is generally followed. The former leverages articulated hand models describing, for example, bones, muscles, and tendons, through kinematics constraints [6,7]; the latter directly exploits depth, RGB-D, or RGB images [8,9,10], to extract keypoints representing a hand. Although both strategies have their merits, data-driven approaches allow the various systems to obtain significant performances while remaining more straightforward to implement, usually resulting in the preferred choice between the two strategies. Moreover, whereas early data-driven works were based on machine learning or computer vision algorithms, such as random forest [11] and geodesic distance-based systems [12], in the latest years the attention has shifted towards deep learning methods [13]. This is a consequence of the high performances obtained in various heterogeneous fields such as emotion recognition [14,15], medical image analysis [16,17], and person re-identification [18,19], as well as the availability of commodity hardware in capture systems [20] that can provide different input types (e.g., depth maps).

Concerning the 3D hand pose estimation, methods based on deep learning architecture configurations, such as multilayer perceptrons (MLPs), convolutional neural networks (CNNs), and autoencoders, have been proposed. These methods usually analyze hand keypoints via 2D heatmaps, representing hand skeletons, extrapolated from depth [8], RGB-D [9], or RGB [21] input images. While the first two input options provide useful information to estimate the 3D pose through the depth component, near state-of-the-art results are obtained exploiting single RGB images [22]. The reason behind this outcome is twofold. First, even though commodity sensors are available, it is hard to acquire and correctly label a depth dataset due to the intrinsic hand skeleton complexity, consequently resulting in a lack of such collections. Second, RGB images can be easily exploited in conjunction with data augmentation strategies, thus allowing a network to be trained more easily [23]. To further improve the 3D hand pose estimation from 2D images, several recent works exploit more complex architectures (e.g., residual network), as well as the multi-task learning paradigm by generating 3D hand shapes together with their estimated pose. Indeed, by leveraging these approaches together with hand models, such as the model with articulated and non-rigid deformations (MANO) [24] and graph CNNs [25], the various systems achieve state-of-the-art performances, produce correct hand shapes, and obtain more accurate pose estimations by an-
alyzing 2D hand heatmaps and depth maps generated from a single RGB input image \cite{26}.

Inspired by the results obtained by other works, in this paper we propose a keypoint-based end-to-end framework obtaining state-of-the-art performances on both 3D hand pose and shape estimation, and show how this system can be successfully applied and outperform other keypoint-based works on another relevant task, i.e., hand-gesture recognition. In detail, the framework comprises a pre-processing phase to normalize RGB images containing hands; a semantic feature extractor implemented through a multi-task stacked hourglass network, employed for the first time in literature to simultaneously generate 2D heatmaps and hand silhouettes starting from an RGB image; a novel viewpoint encoder that sensibly reduces the number of parameters required to encode the feature space representing the camera view during the viewpoint vector computation; a stable hand pose/shape estimator based on a fine-tuned MANO layer employed jointly with an improved version of a neural 3D mesh renderer \cite{27}, extended via a custom weak perspective projection through the 2D re-projection of the generated 3D joint positions and meshes; and a multi-task loss required to train the various framework components to address the 3D hand pose and shape estimation.

To conclude, the main contributions of this paper can be summarized as follows:

- presenting a comprehensive end-to-end framework based on keypoints that merges and improves upon different technologies to generate 3D hand pose and shape estimations;
- proposing a multi-task semantic feature extractor, designing an optimized viewpoint encoder, and introducing a re-projection procedure for more stable outputs;
- evaluating the model generalization capabilities on the hand-gesture recognition task, also outperforming other relevant keypoint-based approaches developed for the 3D hand estimation.

The rest of this paper is organized as follows. Section 2 introduces relevant methods that inspired this work. Section 3 presents an exhaustive description of the framework components. Section 4 shows the experiments performed to validate the proposed approach, and a comparison with other state-of-the-art works on both hand pose and shape estimation as well as hand-gesture recognition tasks. Finally, Section 5 draws some conclusions on this study.

2. Related Work

Methods for 3D pose and shape estimation generally exploit depth, RGB-D or RGB images. The latter is usually the preferred solution due to dataset availability; however, approaches leveraging depth information provide solutions and ideas that can be applied to standalone RGB images as well. For instance, \cite{28}, starting from depth maps, obtain 3D poses by introducing a hierarchical regression algorithm that describes hand keypoints through geometric properties, dividing meaningful hand components such as hands and palm. \cite{29}, instead, use depth maps to build both 3D hand shapes and surfaces by defining 3D voxelized depth maps that allow to mitigate possible depth artifacts. Representing meaningful hand components and reducing input noise are also relevant problems for RGB and RGB-D images. For example, when considering RGB-D inputs for the 3D hand pose estimation task, \cite{30} and \cite{31} define, on the depth component, hand characteristics through geometric primitives that are later matched with the RGB information to generate 3D poses and, ultimately, track the hands. Specifically, spheres, cones, cylinders and ellipsoids are used to describe palm and fingers in \cite{30}, while \cite{31} employ only sphere primitives for faster computation. Differently, \cite{9} focus on handling input noise by using synthetic RGB-D images to train a CNN. In particular, by using artificial RGB/depth image pairs, the authors are able to mitigate the effects of missing or unlabeled depth datasets.

Works exploiting depth information are inherently more suitable to address the 3D pose estimation task since they suffer less from image ambiguities with respect to systems based exclusively on RGB images. To retain depth information without directly using this type of data, \cite{21} introduce a 2.5D representation by building a latent depth space via an autoencoder. Moreover, the authors further refine this latent space through an element-wise multiplication with 2D heatmaps to increase the depth consistency and obtain realistic 3D hand poses. Another work focusing on depth retention without using the extra information at test time, is the one presented by \cite{32}. In the latter, a conditional variational autoencoder (VAE) is first employed to build a latent distribution of joints via the 2D heatmaps, extracted from the input RGB image; a weak-supervision approach is then exploited through a depth regularizer that forces the autoencoder, during training time, to also consider automatically generated depth information in its latent space. A similar weak-supervision rationale is also applied by \cite{26} where, other than depth information, the hand shape consistency is evaluated through a neural renderer. Specifically, exploiting the MANO layer outputs (i.e., 3D hand pose and mesh), the authors project the 3D joint coordinates defining the hand pose into a 2D space, to account for depth information, and implement a neural renderer to generate silhouettes from hand shapes, to increase the hand consistency. This procedure is further refined in the presented work via the weak re-projection applied to both 3D joint locations and mesh, so that the proposed framework could also be applied to a different task.

Accounting for depth information without directly using such data, enables for higher performances when analyzing only RGB images. However, this image format presents several challenges that must be addressed, such as different camera view parameters, background clutter, occlusions, or the hand segmentation. Generally, to handle these problems, RGB-based methods define a pipeline comprising: a feature extraction from the input image, usually in the form of 2D heatmaps; a latent space representation of such features to extrapolate meaningful view parameters; and the 3D hand pose estimation through the computed view parameters. \cite{33}, for instance, implement a CNN called HandSegNet to identify hand silhouettes so that
the input images can be cropped and resized around the hand. A second CNN, defined PoseNet, is then used to extract features, i.e., 2D heatmaps, that allow the network to estimate the 3D pose via a symmetric stream analyzing the pose prior together with the latent pose representation derived by the network. Instead, devise a domain adaptation strategy where a generative adversarial network (GAN), driven by the 2D heatmaps extracted from the input by a convolutional pose machine, automatically outputs hand-only images starting from hand-object ones. The resulting hand-only image is then used to estimate the correct 3D pose even in case of occlusions (e.g., from the object being held).

Specifically, the authors describe 2 parallel encoders to obtain latent representations of both hand and object, which are in turn employed to define meaningful hand-object constellations via a custom contact loss, so that consistent 3D hand poses can be generated. Instead, directly address background clutter and different camera view parameters by designing a disentangling VAE (dVAE) to decouple hand, background, and camera view through a latent variable model so that a MANO layer can receive the correct input to generate the 3D hand pose. What is more, through the dVAE the authors can also synthesize realistic hand images in a given 3D pose, possibly also alleviating the low number of available datasets issue.

Following the aforementioned pipeline allows models to achieve state-of-the-art performances on the 3D hand pose estimation task. Nevertheless, depending on the 3D joint position generation procedure, a good latent space representation becomes a requirement to have an effective system. For example, utilize a stacked hourglass to retrieve 2D heatmaps from the input RGB image. A residual network is subsequently implemented to generate a meaningful latent space, later employed to build a graph CNN defining both 3D pose and shape of the input hand. Moreover, to further improve the obtained results, the authors pre-train all networks on a synthetic dataset before fine-tuning them on the estimation task. Differently from the work introduced by [25], which is used as a starting point, the presented framework further extends the stacked hourglass and residual network by defining a multi-task semantic feature extractor and viewpoint encoder, respectively. Moreover, only the multi-task feature extractor is pre-trained on synthetic data so that the viewpoint encoder is able to obtain a hand abstraction that can be utilized in a different task such as hand-gesture recognition.

Finally, the latent space representation is also relevant when using other procedures for the 3D pose estimation, such as the MANO layer, as discussed by [37] and [38]. In detail, the former work extracts 2D heatmaps via a CNN, then employs an encoder to directly generate the MANO layer view parameters; in the latter approach, instead, a latent space is built by an evidence estimator module leveraging the pose estimation network devised by [39] (i.e., a convolutional pose machine), which generates the required parameters for the MANO layer. What is more, both methods implement a re-projection procedure of the 3D joints, further extended by [38] via an iterative re-projection, to improve the final 3D hand pose and, consequently, shape estimations. To better exploit this interesting strategy, in the presented framework, differently from these two approaches, the re-projection procedure is also applied to the mesh generated by the MANO layer so that the estimation could benefit from both outputs instead of only the 3D locations.

3. Method

The proposed framework for 3D hand pose and shape estimation, starting from a pre-processed hand image input, first generates 2D heatmaps and hand silhouettes through the multi-task semantic feature extractor. Second, by exploiting the semantic features, it estimates the camera, hand pose, and hand shape view parameters through the viewpoint encoder. Finally, by using these parameters, it computes the hand 2D and 3D joints, its mesh and silhouette through the MANO layer, weak perspective projection and neural renderer components. Notice that a single compound loss function is employed to jointly drive the learning phase of the various modules. The framework pipeline is summarized in Fig. 1.

3.1. Pre-processing

A required step to handle different image sizes and reduce the amount of background clutter for samples in a given dataset, is the input image pre-processing. Specifically, to allow the proposed framework to focus on hands, all images are modified so that the hand is always centered and there is as little background as possible, while still retaining all of the 21 hand joints keypoints. In detail, the hand is centered by selecting the middle finger metacarpophalangeal joint (i.e., the base knuckle) as
3.2. Semantic Feature Extractor

Inspired by the results obtained by [25], we implemented a modified version of a stacked hourglass network [40] to take advantage of the multi-task learning approach. In particular, 2D heatmaps and hand silhouette estimates are generated starting from the 256 × 256 × 3 normalized (i.e., with zero-mean and unit variance) image $I_{\text{normalized}}$. The hourglass architecture was selected since it allows to capture many features, such as hand orientation, articulation structure, and joint relationships, by analyzing the input image at different scales. In detail, in the proposed architecture 4 convolutional layers are employed to reduce the input image down to a size of 64 × 64 via two max pooling operations at the first and third layers. The downsized images are subsequently fed to the first hourglass module so that intermediate heatmaps and silhouette are generated by processing both local and global contexts in a multi-task learning scenario. These two outputs, of size $64 \times 64 \times 21$ (i.e., one channel per hand joint) and $64 \times 64 \times 2$ (i.e., back and foreground channels) for 2D heatmaps and silhouette, respectively, are then mapped to a larger version of a stacked hourglass network via a 1×1 convolution to reintegrate the intermediate feature predictions into the feature space. Moreover, these representations are summed together with the hourglass input into a single vector $f$, effectively introducing long skip connections to reduce data loss for the second hourglass module. Finally, this second module is employed to extract the semantic feature vector $f$ containing the effective 2D heatmaps and hand silhouette used by the viewpoint encoder to regress camera view, hand pose and hand shape parameters. Notice that, contrary to $f$, the vector $\hat{f}$ is computed via concatenation of 2D heatmaps, hand silhouette, and $\hat{f}$, providing the viewpoint encoder with a comprehensive representation of the input.

3.3. Viewpoint Encoder

The extracted semantic feature vector $f$ is resized to a shape of 256 × 256 and is then used as input for the second framework component, i.e., the viewpoint encoder, which has two main objectives. First, this unit has to generate a set of parameters $\nu$, employed by the last pipeline component to produce the 3D hand pose and shape. Specifically, vector $\nu$ contains the camera view translation $t \in \mathbb{R}^2$, scaling $s \in \mathbb{R}^+$, and rotation $R \in \mathbb{R}^3$, as well as the hand pose $\theta \in \mathbb{R}^{45}$ and shape $\beta \in \mathbb{R}^{10}$ values necessary to move from a 2D space to a 3D one. Second, the viewpoint encoder also needs to sensibly reduce the number of trainable parameters of the architecture to satisfy hardware constraints. In detail, given the semantic fea-
ture vector \( f \), a flattened latent viewpoint feature space \( l_v \), encoding semantic information, is obtained by using 4 abstraction blocks each containing 2 residual layers [41], to analyze the input, and a max pooling layer, to both consolidate the viewpoint blocks each containing 2 residual layers [41], to analyze the in-
coding semantic information, is obtained by using 4 abstraction

\[ v \times \] put, and a max pooling layer, to both consolidate the viewpoint blocks each containing 2 residual layers [41], to analyze the in-

\[ v \in \mathbb{R}^{64}, \] by employing 3 dense layers to elaborate on the rep-

\[ v \] resentation derived by the residual layers. Notice that by employ-

\[ v \] ing a max pooling layer inside each abstraction block, a smaller latent space is obtained and, consequently, a lower amount of parameters has to be trained; therefore, both objectives for this module are achieved. Finally, the entire viewpoint encoder architecture is shown in Fig. [3]

3.4. Hand Pose/Shape Estimator

The last framework component utilizes the set of parameters \( v = [t, s, R, \theta, \beta] \) to exploit the hand pose and shape. In par-

\[ v \] ticular, the estimator exploits a MANO layer for the 3D joint positions and hand mesh generation. Moreover, these outputs are improved during training by leveraging a weak perspective projection procedure and a neural renderer that enable for more accurate estimations.

3.4.1. MANO Layer

This layer models hand properties such as finger slenderness, palm thickness, as well as hand pose, and controls the 3D surface deformation from articulations. Formally, given the pose \( \theta \) and shape \( \beta \) parameters, the MANO hand model \( M \) is defined as follows:

\[ M(\beta, \theta) = W(T_p(\beta, \theta), J(\beta), \theta, \beta, W), \] (2)

where \( W \) is a linear blend skinning (LBS) function [42]; \( T_p \) cor-

\[ T_p \] esponds to the articulated mesh template to blend, composed by \( K \) joints; \( J \) represents the joint locations learnt from the mesh vertices via a sparse linear regressor; and \( W \) indicates the blend weights.

To avoid common problems of LBS models, such as overly smooth outputs or mesh collapse near joints, the template \( T_p \) is obtained by deforming a mean mesh \( \tilde{T} \) using the pose and blend functions \( B_S \) and \( B_P \) with the following equation:

\[ T_p = \tilde{T} + B_S(\beta) + B_P(\theta), \] (3)

where \( B_S \) and \( B_P \) allow to vary the hand shape and to cap-

\[ B_S(\beta) = \sum_{n=1}^{\#} \beta_n S_n, \] (4)

\[ B_P(\theta) = \sum_{n=1}^{9K} (R_n(\theta) - R_n(\theta^*)) P_n, \] (5)

where \( S_n \in S \) are the blend shapes computed using principal component analysis (PCA) on a set of registered hand shapes, normalized by a zero pose \( \theta^* \); \( 9K \) represents rotation matrix scalars for each of the \( K \) hand articulations; \( R_n \) indicates the \( n \)-th element rotation matrix coefficients; while \( P_n \in P \) corresponds to the blend poses. Finally, in a human population hand shapes variability naturally occurs and, consequently, possible skeleton mismatches might be found in the MANO layer 3D joint output. To address this issue, the adapt skeleton procedure was implemented following the solution devised by [33]. Specifically, the skeleton adaptation is obtained via a linear layer initialized to the identity function, mapping the MANO joints to the final joint annotations.

3.4.2. Weak Perspective Projection

The weak perspective projection procedure takes as inputs the translation vector \( t \), scalar parameter \( s \), and the 3D hand pose \( R(\beta, \theta) \) derived from the MANO model \( M(\theta, \beta) \), to re-

\[ w_{2D} = \Pi(RJ(\beta, \theta))) + t, \] (6)

where \( \Pi \) corresponds to the orthographic projection.

3.4.3. Neural Renderer

To improve the mesh generated by the MANO layer, the differentiable neural renderer devised by [27], thus trainable via back-propagation, is employed to rasterize the 3D shape into a hand silhouette. This silhouette, similarly for the re-projected hand joint coordinates, is subsequently used to improve the mesh generation itself. Formally, given a 3D mesh, composed by \( N = 778 \) vertices \( \{v_1, v_2, \ldots, v_{778}\} \), with \( v_i \in \mathbb{R}^3 \), and \( M = 1538 \) faces \( \{f_1, f_2, \ldots, f_{1538}\} \), with \( f_i \in \mathbb{N}^3 \), the vertices are first projected onto the 2D screen space using the weak perspective projection via the following equation:

\[ v_i^\prime = \Pi(Rv_i^\prime) + t, \] (7)

where \( R \) corresponds to the rotation matrix used to build the MANO hand model \( M(\beta, \theta) \). The rasterization is then applied to generate an image from the projected vertices \( v_i^\prime \), and faces \( f_j \), where \( i \in N, j \in M \), via sampling; as explained by [27]. Specifically, the latter designed different gradient flow rules to handle vertices residing outside, or inside, a given face. For ease of explanation, only the \( x \) coordinate of a single vertex \( v_i^\prime \), and a pixel \( P_j \), are considered in both scenarios. Notice that the color of \( P_j \) corresponds to a function \( I(x_i) \), defined by freezing all variables but \( x_i \) to compute the partial derivatives.

Concerning \( P_j \) resided outside the face, the gradient flow rule is defined as follows:

\[ \frac{\partial I(x_i)}{\partial x_i} \bigg|_{x_i=x_{ij}} = \begin{cases} \delta_i^j, & \text{if } \delta_i^j \delta_j^i < 0; \\ \delta_j^i, & \text{if } \delta_i^j \delta_j^i \geq 0, \end{cases} \] (8)
where $\delta_i^t = x_i - x_0$ indicates the distance traveled by $x_i$ during the rasterization procedure; $\delta_j^f = I(x_j) - I(x_0)$ represents the color change; while $\delta_j^p$ corresponds to the error signal back-propagated to pixel $P_j$. Notice that the derivative with respect to $y_i$ is obtained by using the y-axis in Eq. \[8\].

Regarding $P_j$ residing inside the face, \[27\] first define the left and right derivatives at $x_0$ as $\delta_{j}^l = I(x_{j}^l) - I(x_0)$, $\delta_{j}^b = I(x_{j}^b) - I(x_0)$, $\delta_{j}^p = x_{j}^b - x_{j}^l$, and $\delta_{j}^p = x_{j}^l - x_0$. Then, similarly to $P_j$ residing outside the face, they define the gradient flow rules as follows:

$$
\frac{\partial I_j(x_i)}{\partial x_i} = \frac{\partial I_j(x_i)}{\partial x_i} + \frac{\partial I_j(x_i)}{\partial x_i}, \quad (9)
$$

$$
\frac{\partial I_j(x_i)}{\partial x_i} = \begin{cases} 
\delta_j^p, & \text{if } \delta_j^b \delta_j^p < 0; \\
0, & \text{if } \delta_j^b \delta_j^p \geq 0,
\end{cases} \quad (10)
$$

$$
\frac{\partial I_j(x_i)}{\partial x_i} = \begin{cases} 
\delta_j^p, & \text{if } \delta_j^b \delta_j^p < 0; \\
0, & \text{if } \delta_j^b \delta_j^p \geq 0.
\end{cases} \quad (11)
$$

### 3.5. Multi-task Loss

The proposed framework final output are the 3D joint positions and the hand mesh. However, in real-world datasets the ground truth for 3D hand mesh, pose, shape, and view parameters, which are unknown in unconstrained situations, are hard to collect. Therefore, the intermediate representations automatically generated by the framework, i.e., 2D heatmaps, hand silhouette, and 2D re-projected joint positions and mesh, are exploited to jointly train the whole system through a single loss function. Formally, the multi-task loss function employed in this work, is defined as follows:

$$
L = L_{SFE} + L_{3D} + L_{2D} + L_{M} + L_{Reg}, \quad (12)
$$

where $L_{SFE}$, $L_{3D}$, $L_{2D}$, $L_{M}$, and $L_{Reg}$ correspond to the semantic feature extractor, 3D joint positions, 2D joint re-projection, hand silhouette mask (i.e., re-projected mesh), and model parameter regularization losses, respectively.

#### 3.5.1. $L_{SFE}$

The semantic feature extractor estimates 2D heatmaps and hand silhouette. The loss for a given hourglass module $h_i$ is defined as the sum of heatmaps $L_h$ and silhouette pixelwise binary cross entropy (BCE) losses, as follows:

$$
L_h = ||H - H||_2^2 + ||M - M||_{BCE}^2, \quad (13)
$$

where $H$ is the hourglass output for the 2D heatmaps $H$ and silhouette mask $M$. Moreover, the 2 stacked hourglass network losses are summed to apply an intermediate supervision since, as demonstrated by \[40\], it allows to improve the final estimates. Thus, the semantic feature extractor loss is defined as:

$$
L_{SFE} = L_{h_1} + L_{h_2}, \quad (14)
$$

#### 3.5.2. $L_{3D}$

An $L_2$ loss is also used to measure the distance between the estimated 3D joint positions $RJ(\beta, \theta)$ and ground truth coordinates $w_{3D}$ as follows:

$$
L_{3D} = ||w_{3D} - RJ(\beta, \theta)||_2^2 \quad (15)
$$

#### 3.5.3. $L_{2D}$

The 2D re-projected hand joint positions loss is used to refine the view parameters $t$, $s$, and $R$, for which the ground truth is unknown, and is computed via:

$$
L_{2D} = ||w_{2D} - \hat{w}_{2D}||_1. \quad (16)
$$

Notice that an $L_1$ loss is used since it is less sensitive and more robust to outliers in comparison with the $L_2$ loss.

#### 3.5.4. $L_{M}$

The silhouette mask $M$ loss is introduced as weak supervision, since the hand mesh should be consistent with its silhouette \[25\] or depth map \[27\]. Therefore, this $L_2$ loss helps to refine both the hand shape and camera view parameters via the following equation:

$$
L_M = ||M - \hat{M}||_2^2. \quad (17)
$$

#### 3.5.5. $L_{Reg}$

The last loss component is a regularization term that tries to reduce the hand model parameters $\beta$ and $\theta$ magnitude, so that unrealistic mesh representations are avoided. Specifically, focusing only on the 2D and 3D joint positions, while ignoring the hand surfaces, results in the mesh fitting joint locations and completely ignoring the hand anatomy. Thus, to avoid possible extreme mesh deformations, a regularization term is considered via:

$$
L_{Reg} = ||\beta||_2^2 + ||\theta||_2^2. \quad (18)
$$

### 4. Experimental Results

This section first introduces the benchmark datasets for 3D hand pose and shape estimation and hand-gesture recognition used to validate the framework, as well as the data augmentation strategy employed to better exploit all the available samples. Subsequently, it shows a comprehensive performance evaluation. Specifically, it presents ablation studies on the single components to highlight the proposed approach effectiveness both quantitatively and qualitatively; a state-of-the-art comparison for the 3D hand pose and shape estimation; and the results obtained on a different task, i.e., hand-gesture recognition, so that the framework abstraction capabilities can be fully appreciated.

#### 4.1. Datasets

Several benchmark datasets are exploited to evaluate the proposed framework, i.e., the synthetic object manipulation (Ob-Man) \[35\], the stereo hand dataset (STB) \[33\], RWTH gesture
(RWTH) [44], and the creative Senz3D (Senz3D) [45] collections. Specifically, ObMan is used to pre-train the semantic feature extractor to generate as accurate as possible 2D heatmaps and hand silhouette estimations; STB is employed to evaluate the 3D hand pose and shape estimations through ablation studies and state-of-the-art comparisons; while RWTH and Senz3D are utilized to assess the framework generalization capabilities on the hand-gesture recognition task.

4.1.1. ObMan
This is large-scale synthetic dataset comprising images of hands grasping different objects, i.e., bottles, bowls, cans, jars, knife, cellphones, cameras and remote controls. Realistic images of embodied hands are built by transferring different poses to hands via the SMPL+H model [24]. Moreover, to provide natural occlusions and coherent backgrounds, different rotation and translation operations are employed to maximize the viewpoint variability. For each hand-object configuration, object-only, hand-only, and hand-object images are generated together with the corresponding segmentation, depth map, and 2D/3D joints location of 21 keypoints. From this collection, 141,550 RGB images of shape 256 × 256, showing either hand-only or hand-object configurations, were selected to train the semantic feature extractor.

4.1.2. STB
This dataset contains stereo image pairs (STB-BB) and depth images (STB-SK) and was devised to evaluate hand pose tracking/estimation difficulties in real-world scenarios. Therefore, 12 different sequences of hand poses were collected using 6 different backgrounds representing static or dynamic scenes. Hand and fingers are either moved slowly or randomly to obtain simple and complex self-occlusions and global rotations. Both collections have the same 640 × 480 resolution, identical camera pose, and similar viewpoints. Furthermore, both subsets contain 2D/3D joint locations of 21 keypoints. From this collection, only the STB-SK subset, divided into 15000 and 3000 samples for train and test sets, respectively, is utilized to evaluate the proposed network.

4.1.3. RWTH
This dataset includes finger spelling gestures from the German sign language. Specifically, it comprises RGB video sequences for 35 signs representing letters from 'A' to 'Z', 'SCH', umlauts '¨A', '¨O', '¨U', and numbers from 1 to 5. For each gesture, 20 distinct persons were recorded twice using two distinct cameras from different viewpoints, at resolutions of 320 × 240 and 352 × 288, for a total of 1400 samples. From this collection, all gestures requiring motion, i.e., 'J', 'Z', '¨A', '¨O', '¨U', were ignored. Thus, the used subset contains 30 static gestures over 1160 images. This collection was divided into disjoint training and test sets containing 928 and 232 images, respectively, in accordance with [33].

4.1.4. Senz3D
This dataset contains 11 different gestures performed by 4 distinct persons. To increase the samples complexity, the authors collected gestures having similar characteristics, e.g., same number of raised fingers, high finger vicinity, and touching fingertips. All gestures were captured through an RGB camera and a time-of-flight (ToF) depth sensor at a resolution of 320×240. Moreover, each gesture was repeated by every person 30 times, for a total of 1320 acquisitions. All of the available samples from this collection were employed in the experiments.

4.2. Data Augmentation
Data augmentation is a common practice that can help a model to generalize the input data and, consequently, be more robust. In this work, up to 4 different groups of transformations, randomly selected during each training phase iteration, can be applied to an input image to further increase their dissimilarities. A list of such transformations follows:

- **blur:** obtained by applying a Gaussian filter with varying strength, via \( \sigma \in [1, 3] \) kernel; or by computing the mean over neighborhoods, using a kernel shape from size 3 × 3 to 9 × 9;
- **random noise:** achieved by adding Gaussian noise to an image, either sampled randomly per pixel channel, or once per pixel from a normal distribution \( \mathcal{N}(0, 0.05 \cdot 255) \);
- **artificial occlusion:** attained by either dropping up (i.e., setting them to black) to 30% contiguous pixels, or by replacing up to 20% pixels using a salt-and-pepper strategy;
- **photometric adjustments:** derived from arithmetic operations on the image matrix by adding a value in a \([-20, 20]\] range to each pixel; by improving or worsening the image contrast; and by changing the brightness by multiplying the image matrix with a value in a \([0.5, 1.5]\) range.

Notice that all transformations only affect an image appearance and leave the 2D/3D coordinates unaltered.

4.3. Performance Evaluation
The presented system was developed using the Pytorch framework. All experiments were performed using an Intel core i9-9900K @3.60GHz CPU, 32GB of RAM, and an Nvidia GTX 1080 GPU with 8GB GDDR5x RAM. Common metrics for 3D hand pose and shape estimation, as well as for hand-gesture recognition, are used to assess the proposed framework, i.e., 3D end-point-error (EPE) and area under the curve (AUC) for the former task, and accuracy for the latter. In detail, the EPE, used in the ablation studies, is defined as the average Euclidean distance, measured in millimetres (mm), between predicted and ground truth keypoints; the AUC, instead, is computed on the 3D percentage of correct keypoints (3D PCK) score at different thresholds, using a range between 20-50mm. Finally, for both metrics, the public implementation by [33] is employed for fair comparisons.
Table 1: Semantic feature extractor ablation study.

| Design choice | EPE |
|---------------|-----|
| No semantic feature extractor (SFE) | 13.06 |
| SFE (heatmaps only) | 11.69 |
| SFE (heatmaps + silhouette) | 11.52 |
| ObMan pre-trained SFE (heatmaps + silhouette) | 11.12 |

Table 2: Viewpoint encoder ablation study.

| Design choice | EPE |
|---------------|-----|
| 2*ResNet modules Viewpoint Encoder | 28.77 |
| 4*ResNet modules Viewpoint Encoder | 11.12 |
| 5*ResNet modules Viewpoint Encoder | 12.25 |
| 3*1024 dense layers Viewpoint Encoder (VE₁) | 10.79 |
| 2*2048/1*1024 dense layers Viewpoint Encoder (VE₂) | 11.12 |
| 3*2048 dense layers Viewpoint Encoder | 11.86 |

4.3.1. Framework Quantitative and Qualitative Results

The introduced framework contains several design choices to obtain stable 3D hand pose and shape estimations. Therefore, ablation studies were performed to assess the effectiveness of each decision. The obtained results are summarized in Table 1, Table 2, Table 3, and Table 4, where each table refers to experiments on a given component, i.e., semantic feature extractor, viewpoint encoder, hand pose/shape estimator, and advanced framework components. All reported EPE scores are computed on the STB dataset, while the SFE unit pre-training was carried out exclusively on the ObMan dataset since it contains a high number of synthetic images under various conditions. For both collections, mini-batches of size 6, and an Adam optimizer with a $10^{-4}$ learning rate and a $10^{-5}$ weight decay were used to train the system. The framework was trained for 60 and 80 epochs on the ObMan and STB datasets, respectively, due to former hand pose estimations. As shown in Table 2, using either a low or high ResNet modules number (i.e., 2 or at least 5) to produce the latent space representation $l_v$, results in an increased EPE score that is easily associated to underfitting and overfitting scenarios. Furthermore, slightly better performances can be achieved by reducing the dense layers size used to build up the vector $v$. However, while the smaller viewpoint encoder (i.e., $VE₁$) can perform better with respect to a bigger one (i.e., $VE₂$), the same does not apply when considering extra steps such as adapt skeleton and hourglass output concatenation (shown in Table 4), suggesting that some information can still be lost.

The third experiment, summarized in Table 3, concerned the hand pose/shape estimator. Specifically, tests were performed on the number of MANO layer parameters, the presented 2D re-projection, and regularization loss. In detail, increasing the number of hand articulations allows, as expected, to obtain more realistic hands and, consequently, more precise estimations when using all 45 values. Applying the proposed 2D re-projection further reduces the EPE score by providing the MANO layer with a direct feedback on its output. Whereas employing the regularization loss results, instead, in a higher keypoint distance; a difference derived from the hand shape collapsing onto itself as shown in the bottom row of Fig. 4.

The fourth and last test, reported in Table 4, dealt with advanced strategies, i.e., the adapt skeleton and hourglass output concatenation instead of summation. The former strategy allows for a significant performance boost (i.e., 2mm less EPE) since it directly refines the 3D joints produced by the MANO layer. The latter approach, i.e., stacked hourglass output concatenation, further improves the system precision by another 0.31mm since it provides the viewpoint encoder with a fine grained input representation. However, this detailed input description requires bigger dense layers, i.e., $VE₂$, in order not to lose any information. Consequently, using smaller dense layers (i.e., $VE₁$) results in an EPE score increase.

Regarding the qualitative results, output dissimilarities for different framework configurations are shown in Fig. 4. Specifically, from the top row to the bottom one, outputs correspond to
the presented framework, framework without 2D re-projection, framework without SFE module, and full framework without regularization loss. As can be seen, the most important component to get coherent hand shapes is the regularization loss since, otherwise, the mesh collapses onto itself to satisfy the 3D joint locations during training time (i.e., bottom row in Fig. 4c and Fig. 4e). What is more, by employing the SFE module (i.e., Fig. 4 first two rows) more accurate 3D joints and shapes are generated since the semantic feature extractor enforces both the correct localization of joints and a more realistic silhouette generation (i.e., Fig. 4b, Fig. 4c, and Fig. 4d). Moreover, by re-projecting the generated 3D-coordinates and mesh, the final 3D joint locations and hand shape (i.e., Fig. 4d and Fig. 4e) are more consistent with both the estimated 2D locations and input image (i.e., Fig. 4b, and Fig. 4a). Finally, to conclude this qualitative evaluation, some examples of failed 3D pose and shape estimations are shown in Fig. 5. As can be seen, even though coherent hand poses and shapes are generated, the framework is not able to produce the correct output due to wrong joint estimations for the 2D joints and silhouette by the semantic feature extractor. Moreover, this preliminary error can be amplified by the subsequent framework modules as can be seen in the discrepancy between 2D and 3D joint locations reported Fig. 5b and Fig. 5d. Indeed, while the loss presented in Section 3.5 ultimately enforces the MANO layer to produce consistent hands, as also discussed for the third experiment, it might also result in an increased 3D joint position estimation inaccuracy to guarantee such a consistency. Furthermore, such an outcome has two implications. First, it indicates that there is still room for improvement, especially for the 2D joints and silhouette estimations that represent the first step in the proposed pipeline. Second, it highlights the effectiveness of introduced framework, which can generate stable 3D representations from RGB images.

4.3.2. 3D Hand Pose/Shape Estimation Comparison

To show the proposed framework effectiveness, a state-of-the-art 3D PCK AUC comparison is summarized in Table 5. As can be seen, the presented system is in line with the top works using only RGB images and outputting both 3D skeleton locations and mesh; indicating that all of the introduced choices allow the framework to generate good estimates using only RGB information. More interestingly, the proposed method can easily outperform systems exploiting depth data, suggesting that the simultaneous use of the multi-task semantic feature extractor, viewpoint encoder, and 2D re-projection, can help to produce correct estimations by compensating for the missing depth information. Specifically, the multi-task SFE enables the implementation of a customized viewpoint encoder that, in opposition to the work of [37], does not require to be pre-trained on a synthetic dataset in order to perform well; nor necessitates to normalize the latent feature space representation through a variational autencoder, that disentangles different factors influencing the hand representation, to obtain accurate 3D hand poses, as instead described by [36]. Furthermore, thanks to the re-projection module, these results are obtained without applying an iterative regression module to the MANO layer.
contrary to \cite{26} and \cite{34}, where progressive changes are carried out recurrently to refine the estimation parameters, thus simplifying the training procedure. What is more, the presented framework solutions allow first, to avoid input assumptions and post-processing operations, as opposed to the majority of literature works where some parameter (e.g., global hand scale or root joint depth) is assumed to be known at test time; and second, to achieve close performances with respect to the best model devised by \cite{25}, even though the latter employs a more powerful solution (i.e., a graph CNN instead of a fixed MANO layer) for the 3D hand pose and shape estimation.

To conclude this state-of-the-art comparison, the 3D PCK curve computed at different thresholds is reported, for several state-of-the-art works, in Fig. 6. As shown, the 3D hand pose and shape estimation task is becoming saturated, and newer works can consistently achieve great performances with low error thresholds. On this account, the presented work is on par with and behaves as the top literature works; further supporting that all of the introduced choices allow the framework to generate good 3D poses and shapes starting from monocular RGB images.

4.3.3. Hand-Gesture Recognition Comparison

To assess the generalization capabilities of the proposed framework, experiments were performed on the RWTH and Senz3D datasets. Since the presented architecture does not include a classification component, it was extended by attaching the same classifier described by \cite{33} to handle the new task. In detail, the classifier takes as input the 3D joint coordinates generated by the MANO layer, and comprises 3 fully connected layers with ReLU activation function. Notice that all weights, except for the classifier ones, are frozen when training the system on the hand-gesture recognition task, so that it is possible to correctly evaluate the framework generalization power. The performed experiments follow the testing protocol devised by \cite{9} to present a fair comparison, i.e., a 10-fold cross-validation with non overlapping 80/20 splits for training and test sets, respectively. All images, similarly to other state-of-the-art works, were cropped near the hand to remove as much background as possible and meet the framework input shape, i.e., 256 × 256. The obtained results are reported in Table 6, where the literature comparison is summarized. As shown, our framework consistently outperforms the other work focusing on the 3D pose and shape estimation (i.e., \cite{33}) on both collections, highlighting that it generates more accurate joint coordinates from the RGB image; a result also reflected on the estimation task, as can be seen in Table 5. However, methods exploiting depth information (i.e., \cite{9}) or concentrating on the hand-gesture classification (i.e., \cite{48}) can still achieve slightly higher performances. This outcome has a twofold explanation. First, by concentrating on the hand-gesture classification task, lower performances are achieved on the estimation task although similar informa-
Table 5: AUC state-of-the-art comparison on STB dataset. Works are subdivided according to their input and output types.

| Model         | Input     | Output        | AUC  |
|---------------|-----------|---------------|------|
| CHPR [28]     | Depth     | 3D skeleton   | 0.839|
| ICPPSO [31]   | RGB-D     | 3D skeleton   | 0.748|
| PSO [30]      | RGB-D     | 3D skeleton   | 0.709|
| Dibra et al. [9] | RGB-D     | 3D skeleton   | 0.923|
| Cai et al. [32] | RGB      | 3D skeleton   | 0.996|
| Iqbal et al. [21] | RGB      | 3D skeleton   | 0.994|
| Hassan et al. [35] | RGB     | 3D skeleton   | 0.992|
| Yang and Yao [36] | RGB     | 3D skeleton   | 0.991|
| Spurr et al. [46] | RGB     | 3D skeleton   | 0.983|
| Zummermann and Brox [33] | RGB | 3D skeleton   | 0.986|
| Mueller et al. [10] | RGB | 3D skeleton   | 0.965|
| Panteleris et al. [47] | RGB | 3D skeleton   | 0.941|
| Ge et al. [25] | RGB      | 3D skeleton+mesh | 0.998|
| Baek et al. [24] | RGB | 3D skeleton+mesh | 0.995|
| Zhang et al. [26] | RGB | 3D skeleton+mesh | 0.995|
| Boukhayma et al. [37] | RGB | 3D skeleton+mesh | 0.993|
| ours          | RGB       | 3D skeleton+mesh | 0.995|

Table 6: Hand-gesture recognition accuracy comparison.

| Model                                      | RWTH   | Senz3D   |
|--------------------------------------------|--------|----------|
| Papadimitriou and Potamianos [48]          | 73.92% | -        |
| Memo and Zanutti [49]                      | 73.60% | 94.00%   |
| Dibra et al. [9]                           | 63.44% |          |
| Soufiani and Brox [33]                     | 66.80% | 77.00%   |
| ours*                                      | 72.03% | 92.83%   |

*method focusing on 3D hand pose and shape estimation

tion, such as the 3D joint locations, are used. As a matter of fact, even though they exploit depth information in their work, [9] obtained a 0.923 AUC score while [33] and the presented framework can reach up to 0.986 and 0.994 AUC scores on the STB dataset for 3D hand pose estimation, respectively. Second, as discussed in Section 4.3.1 and shown by the qualitative results in Fig. 5, the proposed architecture can still be improved by increasing the 2D joints and silhouette estimation accuracy; indicating that a good hand abstraction used to derive 3D hand pose and shape can, in fact, be effective to address the hand-gesture recognition task.

Summarizing, the proposed method achieves state-of-the-art performances on the 3D hand pose and shape estimation task, can outperform other existing estimation approaches when applied to the hand-gesture recognition task, and behaves considerably to other specifically designed hand-gesture recognition works; thus indicating that the introduced pipeline outputs stable hand pose estimations that can be effectively applied to recognize hand-gestures.

5. Conclusion

In this paper we presented an end-to-end framework for the 3D hand pose and shape estimation and effectively applied it to the hand-gesture recognition task. As demonstrated by the experimental results, the multi-task semantic feature extractor, viewpoint encoder, and hand pose/shape estimator with weak re-projection, designed by exploiting and extending literature strategies, are able to achieve state-of-the-art performances on the 3D hand pose and shape estimation task. Moreover, when addressing the hand-gesture recognition task, the same framework outperforms, on both the presented benchmark datasets, other works that were devised for the estimation task and later employed to recognize hand-gestures.

As future work, further upgrades to the semantic feature extractor are already planned to first, increase its 2D heatmaps and silhouette estimation accuracy and second, generate other meaningful features extending the multi-task strategy. Moreover, further experiments on the abstraction capabilities will be performed by retaining also the 3D shape when moving to the hand-gesture recognition task, hopefully improving the final obtained results.

References

[1] P. C. Madhusudana, R. Soundararajan, Subjective and objective quality assessment of stitched images for virtual reality, IEEE Transactions on Image Processing 28 (11) (2019) 5620–5635. doi:10.1109/TIP.2019.2921858.
[2] M. Makar, V. Chandrasekhar, S. S. Tsai, D. Chen, B. Girod, Interframe coding of feature descriptors for mobile augmented reality, IEEE Transactions on Image Processing 23 (8) (2014) 3352–3367. doi:10.1109/TIP.2014.2331136.
[3] D. Avola, M. Bernardi, L. Cinque, G. L. Foresti, C. Massaroni, Exploiting recurrent neural networks and leap motion controller for the recognition of sign language and semaphoric hand gestures, IEEE Transactions on Multimedia 21 (1) (2018) 234–245. doi:10.1109/TMM.2018.2856094.
[4] X. Liu, H. Shi, X. Hong, H. Chen, D. Tao, G. Zhao, 3d skeletal gesture recognition via hidden states exploration, IEEE Transactions on Image Processing 29 (2020) 4583–4597. doi:10.1109/TIP.2020.2974061.
[5] J. M. Rehg, T. Kanade, Visual tracking of high dof articulated structures: an application to human hand tracking, in: Proceedings of the European
[41] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778. doi:10.1109/CVPR.2016.90

[42] M. Loper, N. Mahmood, J. Romero, G. Pons-Moll, M. J. Black, Smpl: A skinned multi-person linear model, ACM Transactions on Graphics 34 (6) (2015) 1–16. doi:10.1145/2816795.2818013

[43] J. Zhang, J. Jiao, M. Chen, L. Qu, X. Xu, Q. Yang, 3d hand pose tracking and estimation using stereo matching, arXiv preprint arXiv:1610.07214 (2016) 1–11.

[44] P. Preusw, T. Deselaers, D. Keysers, H. Ney, Modeling image variability in appearance-based gesture recognition, in: Proceedings of the European Conference on Computer Vision Workshops: Workshop on Statistical Methods in Multi-Image and Video Processing (ECCVW), 2006, pp. 7–18.

[45] L. Minto, P. Zanuttigh, Exploiting silhouette descriptors and synthetic data for hand gesture recognition, STAG: Smart Tools & Apps for Graphics 1 (0) (2015) 1–9. doi:10.2312/stag.20151288

[46] A. Spurr, J. Song, S. Park, O. Hilliges, Cross-modal deep variational hand pose estimation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 89–98. doi:10.1109/CVPR.2018.00017

[47] P. Panteleris, I. Oikonomidis, A. Argyros, Using a single rgb frame for real time 3d hand pose estimation in the wild, in: Proceedings of the IEEE Winter Conference on Applications of Computer Vision (WACV), 2018, pp. 436–445. doi:10.1109/WACV.2018.00054

[48] K. Papadimitriou, G. Potamianos, Fingerspelled alphabet sign recognition in upper-body videos, in: Proceedings of the European Signal Processing Conference (EUSIPCO), 2019, pp. 1–5. doi:10.23919/EUSIPCO.2019.8902541

[49] A. Memo, P. Zanuttigh, Head-mounted gesture controlled interface for human-computer interaction, Multimedia Tools and Applications 77 (1) (2018) 27–53. doi:10.1007/s11042-016-4223-3