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MODELING OF TEXT RECOGNITION IN IMAGES

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Abstract
We distinguish between perceptual and physical texture differences: the former differences are those perceived by humans, while the latter, on which we concentrate, are those defined by differences in the processes that create the texture in the scene. The task of texture segmentation is to identify image curves that separate different textures. To segment textured images, one must first be able to discriminate textures. A segmentation algorithm performs texture-discrimination tests at densely spaced image positions, then interprets the results to localize edges. This article focuses on the first stage, texture discrimination.

Keywords: Images, textures, segment, while the latter, segmentation, modeling, natural and pedagogic systems.

Introduction

Modeling the recognition of textures in images is an exposure texture We distinguish between perceptual and physical texture differences: the former differences are those perceived by humans, while the latter, on which we concentrate, are those defined by differences in the processes that create the texture in the scene. Physical texture discrimination requires computing image texture measures that allow the inference of physical differences in texture processes, which in turn requires modeling texture in the scene. We use a simple texture model that describes textures by distributions of shape, position, and color of substructures. From this model, a set of image texture measures is derived that allows reliable texture discrimination. These measures are distributions of overall substructure length, width, and orientation; edge length and orientation; and differences in averaged color. Distributions are estimated without explicitly isolating image substructures. Tests of statistical significance are used to compare texture measures.A forced-choice method for evaluating texture measures is described. The proposed measures provide empirical discrimination accuracy of 84 to 100% on a large set of natural textures. By comparison, Laws' texture measures provide less than 50% accuracy when used with the same are estimated without explicitly isolating image substructures. Tests of statistical significance are used to compare texture measures.A forced-choice method for evaluating texture measures is described. The proposed measures provide empirical discrimination accuracy of 84 to 100% on a large set of natural textures. By comparison, Laws' texture measures provide less than 50% accuracy when used with the same ncreasingly, models of the world are directly built fromimages. The paper discusses a number of recent developments that try to push the enveloppe of what image-basedmodeling can achieve. In particular, the analysis of 3D sur-face deformations is discussed for face animation, the ex-traction of matches under wide baseline conditions for 3Dscene reconstruction, and the synthesis of viewpoint depen-dent textures for realistic object rendering.1 Image-based modelingDuring the last few years, low-cost and user-friendly so-lutions for 3D modeling have become available. Shape-from-video [13, 23, 12] extracts 3D shapes and their tex-tures from video sequences as the only input. One-shotstructured light techniques [33, 24] get such informationfrom a single image, but need the projection of a specialpattern. These techniques have the advantage that theyare cheaper than traditional solutions like dedicated multi-camera rigs or laser scanners, as they only require off-the-shelf hardware. Moreover, they offer more flexibility interms of portability and the range of object sizes they canhandle.This paper presents ongoing work on three extension ofsuch systems.Deformable shapes: The detailed capture of deformable3D shapes is to a large extent still an open challenge.We discuss preliminary results for faces. Based on aone-shot, structured light method, 3D deformations areextracted. In particular, face dynamics during speechare acquired, analysed, and resynthesised for anima-tion.Wide-baseline matching: Shape-from-video requireslarge overlap between subsequent frames. Often, onewould like to reconstruct from a small number ofstills, taken from very different viewpoints. Basedon local, viewpoint invariant features, wide-baselinematching ia made possible, and hence the viewpointscan be farther apart.3D textures: Texture mapping is an old trick to hide theabsence of geometric detail. A serious shortcomingof traditional texture mapping is that changing self-occlusions and shadows which result from changingviewpoint or illumination resp. cannot be simulated.Based on a series of views of a textured surface, a tex-ture model is extracted, that captures viewpoint depen-dencies of the surface's appearance.2 Face animationRealistic face animation still is a challenge. Faces are thefocus of attention for human observers, and even the small-est deviations from real speech are noticed. One has to dealwith subtle effects, that leave strong impressions. Althoughrecent computer animation movies have shown convincingresults, there still is a lot of manual work involved.When using 3D modeling for face animation, the syn-thesis can simulate the underlying anatomy of a face, oronly generate the exterior, visible shape. If one can modelthe anatomy really well, one has very good control overthe face, even for expressions that have not been observedbefore. With its many muscles, the face anatomy is verycomplicated, however. Work on emotional expressions byPighin et al. [22] has demonstrated that realistic anima-tion can also be achieved without such detailed knowledge.Their animations are based solely on observed, exterior faceshape. These represent a kind of keyframes, between whicha linear morph is applied.Here a similar approach is presented – that is also onlybased on the extraction of exterior shapes – but for the moresubtle case of speech animation. This is a harder problemthan emotions as higher levels of geometric detail are re-quired. Moreover, simple morphs between mouth positionsdo not capture the subtle co-articulation effects of fluentspeech. Our work is not the first attempt (see e.g. [25]),

The purpose of the work seems to be more automated and based on data of higherspatiotemporal resolution.2.1 Extracting example visemesAnimation of speech has much in common with speechsynthesis. Rather than composing a sequence of phonemesaccording to co-articulation principles, animation generatessequences of visemes. These are the basic mouth deforma-tions during speech. Whereas there is a consensus about theset of phonemes, there is less unanimity about the selectionof visemes. There is no one-to-one relation between the 52phonemes and the visemes, as different sounds may lookthe same and v.v. Realistic animation experiments haveused any number from as few as 16 [9] up to about 50visemes [26]. At least as important are the co-articulationprinciples that are used.We based our selection of visemes on the work ofOwens [21] for consonants. We use his consonant groupsthat yield the same visual impression when uttered, but donot consider all the possible instances of different, neigh-boring vocals that he mentions. In fact, we only con-sider two cases: rounded and widened, that represent theinstances farthest from the neutral expression (lips closedand relaxed). For the visemes that correspond to vocals,we used those proposed by Montgomery and Jackson [18].This leads to a total of 20 visemes: 12 representing theconsonants, 7 representing the monophtongs, and one rep-resenting the neutral pose. This viseme selection differsfrom others proposed earlier. It contains more consonantvisemes than most, mainly because the distinction betweenthe rounded and widened shapes is made systematically.This selection seems to be a good compromise between thenumber of visemes and the realism that is obtained.The face deformations corresponding to these visemeshad to be analysed carefully. These deformations were ex-tracted for faces of different age, race, and sex. Speech af-fects the entire facial structure below the eyes [19]. There-fore, we extracted 3D data for a complete face, but withemphasis on the area between the eyes and the chin. The3D viseme extraction follows a number of steps, which arerepeated for the different example faces.The process starts with that every test subject says a sen-tence, that contains all the visemes at least once, but typi-cally twice or more. This is captured in 3D using Eyetron-ics' ShapeSnatcher system [8] It projects a grid onto theface, and extracts the 3D shape and texture fromET a singleimage. By using a video camera, a quick succession of 3Dsnapshots can be acquired. We are especially interested inframes that represent the different visemes. These are theframes where the lips reach their extremal positions for thatsound (Ezzat and Poggio [9] followed the same approachin 2D). The acquisition system yields the 3D coordinates ofFigure 1. 3D Snapshots of a talking face, for one ofthe test subjects.Figure 2. Left: generic head model, Right: underly-ing mesh. This generic head model has been producedby Duran (the outer skin) and by Imagination in Mo-tion (tongue and teeth), in the context of the EuropeanMesh project.thousands of points for every frame. The output is a con-nected, triangulated and textured surface. Fig. 1 shows afew 3D snapshots obtained from such an acquisition ses-sion.The problem is that the 3D points correspond to pro-jected grid intersections, not corresponding, physical pointson the face. Hence, the points for which 3D coordinates aregiven change from frame to frame. The next steps have tosolve for the physical correspondences.Physical correspondences are solved by mapping the 3Ddata onto a generic head mesh. This is a triangulated surfacewith 2268 vertices for the skin, supplemented with seper-ate meshes for the eyes, teeth, and tongue (another 8848,mainly for the teeth). Fig. 2 shows the generic head andits topology. This generic head model is fitted to the 3Ddata of the example face (i.e. 3D neutral face data of oneof the test subjects) in a total of three steps.

The first stepin this fitting procedure deforms the generic head by a sim-ple rotation, translation, and anisotropic scaling operation,to crudely align salient features like eye corners, nose tip Figure 3. Four visemes for one of the test subjects.etc., with those on the neutral shape of the example face.After this initial transformation, the salient features are bet-ter aligned through a piecewise constant, vertical stretch in5 facial regions: from top-of-head to eyebrows, from eye-brows to eye corners, from eye corners to nose tip, fromnose tip to mouth corners, and from mouth corners to bot-tom of the chin. The third step performs a local morph. Thismorphing maps the topology of the generic head preciselyonto the example shape. In order to ease this mapping, theexample faces had about 100 points marked as black dots.These three steps are only applied once to the neutralface of a test person. From the initial, neutral frame thepoints are tracked throughout the video and the mesh adaptsautomatically to subsequenct 3D snapshots for non-neutralposes. The special facial features and the marked pointswere extracted in 3D from all frames, the mesh was de-formed to keep these points aligned, and intermediate meshpoints were positioned with the help of Radial Basis Func-tions [20] and projection onto the measured 3D surface.In order to get the catalogue of 3D visemes for a singletest person, the corresponding frames were selected fromthe video and their 3D meshes were averaged over differ-ent instances of the same viseme and stored. A number ofvisemes for one of the example faces is given in fig. 3. Asa matter of fact, not the 3D meshes themselves were stored,but the difference with respect to the neutral one for thesame person. These deformation fields of a single personstill contain a lot of redundancy. This was investigated byapplying a Principal Component Analysis. Over 99% of thevariance in the deformation fields was found in the spacespanned by the first 6 components. This space is referred toas the ‘Viseme Space’ of the person.2.2 Bringing faces to lifeThe previous section described an approach to extracta set of visemes from talking faces, observed with theShapeSnatcher system. This section describes how novel,static 3D face models, for which no such information isavailable, can be animated.Such animation requires a number of steps:personalising the visemes: a set of visemes, adapted tothe physiognomy of the novel face is generated;automatic, audio-based animation: from spoken text atime stamped sequence of visemes is generated, thatdrives the animation;possibly modifications by the animator: ICA based toolsallow the animator to modify the result.A good animation requires visemes that are adapted tothe shape or ‘physiognomy’ of the face at hand. One cannotsimply copy or ‘clone’ the deformations that have been ex-tracted from one of the example faces. The adapted visemesare created in a simple way, that in fact needs further val-idation. Faces can be efficiently represented as points in aso-called ‘Face Space’ [4]. These points represent their de-viation from the average face along some principal modes.Hence, the novel face as well as the neutral, example facescorrespond to such points. The example faces span a hyper-plane in face space. By orthogonally projecting the novelface onto this plane, a linear combination in terms of theexample faces is found, that comes closest to the novel face.This procedure is illustrated in fig. 4 and yields weights thatcan be applied to the visemes of the example faces to gen-erate a set for the novel face.Once the personalised viseme set has been produced, anIndependent Component Analysis (ICA) is applied to them.The visemes are represented as points in their 6D IC space,coined ‘Viseme Space’. Animation then amounts to navi-gating through this space, from viseme to viseme. This iswhere the issue of co-articulation pops up. Visemes exertmutual influences, i.e. the way in which we move our lipsfor a certain vocal or consonant is also dependent on the pre-vious and subsequent sounds.This is similar to spline fit-ting, where surrounding points influence how close a pointis approached, under what orientation the trajectory passes,etc. The audio track that drives the animation specifies the Figure 4. Visemes are adapted to the face physiog-nomu by comparing it to faces for which visemes havebeen extracted (see text).visemes and their timing, but still has to be translated intoa precise trajectory in Viseme Space. In our animation thetrajectory is modeled as a NURBS, attracted with differ-ent strengths towards the different visemes along its path.These differences in strength reflect the variability in differ-ent viseme shapes. There is much more room for changewhen pronouncing ‘d’ than there is for ‘m’, for instance.A distinction is made between vocals and labial consonantson the one hand, and the remainder of the visemes on theother. The former impose their deformations much morestrictly onto the animation than the latter, which can be pro-nounced with a lot of visual variation. In terms of the splinefitting this means that the animation trajectory will moveprecisely through the former visemes and will only be at-tracted towards the latter. The strength of this attractiondiffers between subclasses of the remaining visemes.The foregoing animation from audio runs automatically.The animator can afterwards still change the influences ofthe different visemes, as well as the complete NURBS thatdefine the trajectory in Viseme Space. We have used in-dependent rather than principal components as they werefound to provide a more intuitive basis.3 Wide-baseline matchingAlthough 3D reconstructions can in principle be madefrom a limited number of stills, fully automated process-ing is only possible if the images have much overlap andare offered in the order of a continuous camera motion. Thename ‘shape-from-video’ underlines this assumption. In or-der to automate similar reconstructions from stills that aretaken from substantially different viewpoints, the computershould find correspondences under ‘wide baseline’ condi-tions. Consider the wide baseline image pair of fig. 5. Thetwo images have been taken from very different viewing di-Figure 5. Two images of the same scene, but takenunder very different viewing directions. The task is tofind an initial set of features, that suffice to extract theepipolar geometry, which can then serve as a supportfor dense correspondence search. Combining a geometry-based approach for the overall shapes of objects with animage-based rendering of the surface details seems to holdgood promise for the realistic visualisation of scenes. Theinteractions with and between the objects is easier to imple-ment, while the photo-realism of the scene rendering can beimproved.The first steps towards multiview texture analysis andsynthesis have already been taken. Firstly, the changes intextures that occur under changing viewpoints and illumi-nations have been recorded systematically for a series ofmaterials [7]. In order to get a handle on these effects,several authors have developed textures descriptions that ei-ther include such changes or are invariant. The outputs ofGaussian derivative filters for different viewing conditionshave been clustered and used for material recognition andreproduction of the same piece of texture [15]. Chantler and coworkers [17] have focused on the effects of chang-ing illumination, both for analysis and synthesis, but do notchoose a purely image-based approach. The approach ofCula and Dana [6] is image-based and is oriented towardstexture classification. In some respect their system comesclose to ours, but we focus on the synthesis of multiviewtextures. An important difference of these approaches withearlier work on bump maps and relief textures is that no 3Dinformation is extracted.4.1 The basic texture modelOur multiview texture model is an extension of a singleview texture modeling technique. The latter extracts somecarefully chosen statistics from an example texture duringan analysis step. Synthesis then consists of constructingtextures with similar statistics. The method has the advan-tage that it can handle both stochastic and structural tex-tures. It does not copy any part of the example texture,thereby avoiding repetitions in the synthesized textures. Itincludes both short-range and long-range pixel interactionsand therefore can pick up small- and large-scale effects.The texture model is also highly compact, only a coupleof Kbytes. These advantages are preserved in the extendedversion that includes viewpoint dependency.The single view modeling step extracts first- and second-order statistics from an example image. The first-orderstatistics correspond to the intensity histograms. Thesecond-order statistics draw upon the cooccurrence princi-ple: for pixel pairs at fixed relative positions the intensitiesare compared. The pixel pairs are called cliques and pairswith the same relative positions form a clique type. Theclique is an ordered pair. Hence, a tail and head pixel can bedistinguished. Instead of storing the complete joint proba-bility distributions for the different clique types, our modelonly stores the histogram of the intensity differences be-tween the head and tail pixels. It is not practical to collectthese second-order statistics for all possible clique types.A selection of clique types is made that together containsufficient information to generate a texture that is perceptu-ally very similar. This selection is described elsewhere [34].There it is also shown how this model can be used to synthe-sise a texture that is similar to the example texture. Sufficeit here to say that the synthesis algorithm tries to generatea texture that has the same intensity difference statistics forthe different clique types in the model. The same paper dis-cusses the generalisation of these principles towards colourtextures.In summary, the basic texture model contains the infor-mation necessary to produce a texture for one viewpoint andillumination direction. This model consists of two types ofinformation. On the one hand, there is the set of cliquestypes, which describe which interactions with neighbouringpixels are taken into account. This set will be referred at asthe neighbourhood system. On the other hand, there is theintensity histogram of the textures, as well as the intensitydifference histograms for the different clique types. Theseintensity statistics are referred to as the statistical parame-ter set.The choice of the neighbourhood system takes farmore time than the extraction of the corresponding statisti-cal parameter set.4.2 Multiview texture modelsThe multiview texture model that we have proposed [34,35], takes the single view model as its point of depar-ture. The adaptations towards different viewing conditionsare twofold. On the one hand, an affine deformation isapplied to the neighbourhood system, in accordance withthe change in viewing direction. Typically, the neighbour-hood system is extracted once from a fronto-parallel viewof the texture. This neighbourhood system is then affinelydeformed in accordance with the slant and tilt angles un-der which other views are taken. Further refinements andchanges in illumination are then taken into account througha complete update of the statistical parameter set for everynovel view: all the histograms are extracted anew for theaffinely deformed set of cliques, from the novel view takenunder known conditions. This is repeated for all such ex-amples, i.e. for all example images for different viewingand/or illumination directions. Complete knowledge aboutthese directions is assumed. The advantage of this multi-view modeling is that it hardly takes longer than the model-ing for a single, overhead view. The neighbourhood systemdoes not have to be selected again, as it is obtained throughsimple deformation. The extraction of the updated statisti-cal parameter sets can be done very quickly.Textures corresponding to unseen viewing conditionscan only be generated in as far as sufficiently similar view-ing conditions have been observed. The neighbourhood sys-tem can be adapted easily, but the statistical parameter sethas to be obtained from interpolation or – and this may bea problem – extrapolation of those observed from similarcases. This interpolation or extrapolation is simplified by aPCA description of the histograms. This leads to very com-pact descriptions of these histograms, as weighted combi-nations of the principal components. Splines fitted to theseweights yield the interpolated (or extrapolated) values. Forthis method to work well, sufficient examples must havebeen provided. An example of multiview texture is givenin fig. 7. The top orange is a real one, the one below is asphere clipped by the same silhouet, and oovered with mul-tiview texture learned from the real on.

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