Generating Tactile Textures using Periodicity Analysis

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***Abstract*—In this work we present an approach to generate a tactile representation from an image that may be a photograph or a scan of cloth. A large class of fabrics can be generated by repetition of a parallelogram primitive. That means there are two non-collinear directions where the pattern is periodically repeated. The method we present is based on analysing the repetitive structure of the sample, that is to find the two principle directions of repetition, and building a model from that analysis. We compare our method to a technique developed by Gang Huang.**

***Index Terms*—haptics, tactile sensations, textures, periodicity analysis, virtual fabrics, Kawabata measurements**

I. Introduction

Over the past few decades the computer has evolved from a mere calculating machine to a complex device that allows us to broaden our view of the world around us. The technology known as Virtual Reality serves as a super-microscope, providing insights in processes we could never perceive using normal senses. Traditionally VR addresses two of our senses: the visual perception and the hearing. The next challenge is to integrate further senses, most notably the haptic and tactile senses that allow us to feel an object, in contrast to more traditional approaches of VR with merely visual and acoustic sensations. This is especially important when we deal with materials like textile tissues or when it comes to design surfaces for furniture or car inventory. A haptic interface could allow for example the textile industry to provide not only a visual glance at their products in an online shop but allow the customer to gather an impression of the haptic quality of a cloth.

The purpose of this paper is to present a new method for automatically generating tactile input from optical scans. These scans can be obtained using affordable hardware. In this work being implemented in the master's thesis of Tjard Köbberling [1] we present an approach to generate a tactile representation from an image that may be a photograph or a scan of cloth. The method is based on analysing the repetitive structure of the sample and building a model from that analysis. To give an impression of the performance of our method we compare it to the similar technique developed by Gang Huang [2], [3] using Kawabata measures. It should be made clear from the start that a technique using optical input can not work if there are (coloured) patterns printed on the cloth or if different colours of threads are used. In order for our method to work we must suppose that the cloth is coloured uniformly, best in some shade of light gray.

II. Related Work

The method we present is based on the generation of appropriate height profiles. It was mainly developed in the work of Schulze [4] using implementations of von Wieding [5] and Peinecke [6]. The idea of periodicity analysis based on co-occurrence matrices is well described in [7], the basic ideas can be found in [8], [9]. Refer to [10] for a comparison with alternative methods.

A different method targeted at the same applications was developed by Gang Huang [2], [3]. Huang uses Kawabata measurements to generate a height profile of a fabric. Similar to our approach this profile is used to create the vibrotactile input for the tactile simulation. We have implemented the technique by Huang and compared the results to our method in this paper.

III. Tactile Textures

Before we start to explain details of our method we need to define the basic principles we are dealing with.

By a *haptic sensation* we mean a sensual impression of a mechanical influence on the body, especially the hands. A special case is a *tactile sensation*: These concern the sensation of pressure, touch or vibration on the skin.

A *texture* is a map assigning certain measures of a quantity to a continuous surface. Formally a texture can be defined as map $t : M \to \mathbb{B}$, where M is any metric space and $\mathbb{B}$ denotes an arbitrary set for the values, for example $\mathbb{B} = \mathbb{R}$. Textures are a way to assign certain attributes to virtually every point of a surface, see [11]. For our applications we use $t : \mathbb{R}^2 \to \mathbb{R}$ to represent textile cloth. Woven textiles are composed using two kinds of threads in different directions, the so called weft and warp directions. This makes them especially easily representable by two-dimensional textures.

If the textile is composed of a uniform pattern, that is by simple repetition of a small part, then it can be represented by a periodic 2D texture. A *periodic nD texture* is a texture that is periodic in n non collinear directions. Formally we have $t(\vec{x}) = t(\vec{x} + \vec{p}_i)$ for all $\vec{x} \in \mathbb{R}^n$ for linearly independent $\{\vec{p}_1, \ldots, \vec{p}_n\}$. Rao [12] suggests, to categorise textures by the degree of symmetry they contain, building a taxonomy of strongly ordered, weakly ordered and unordered textures. Particularly, if a texture is periodic with only minor unordered aspects, then it can be approximated by a primitive element having the size of the parallelogram generated by its periodicity directions $\{p_1, \ldots, p_n\}$. An arbitrary part of the texture being such a parallelogram can be used to synthesise the whole texture by just repeating the primitive, see [7]. This is the core idea of this paper: Using a photography of a textile we extract a primitive for this texture. All the haptic information needed should be contained in this primitive. We then have to deal with the problem of converting the optical information captured by the camera to tactile information useful for rendering a realistic tactile impression.

IV. Image Analysis

Our method is based on using optical scans of cloth. These scans can be gathered low cost imaging hardware, for example, optical scanners or digital cameras. We do not suppose that the cloth must be properly aligned along scanner axes. The only prerequisite implied is that the image must be taken from an orthogonal view so that that the image of the cloth is not skewed in any way.

In order to generate a tactile sensation from an optical image we need to reduce the texture to its primitive and then reconstruct the three dimensional geometric structure of the textile. We accomplish the first task by symmetry extraction using statistical feature matrices, the second by using the well known *shape from shading* method.

A. Primitive Extraction

To extract a primitive from a given, possibly distorted image, we need to make a guess about the two directions of periodicity. This can be done using a special statistical feature matrix, the autocorrelation matrix AM. We define AM by:

$$AM_{\vec{p}} := \rho(t(\vec{x}), t(\vec{x} + \vec{p}))$$

with ρ being the correlation coefficient:

$$\rho(t(\vec{x}), t(\vec{x} + \vec{p})) = \frac{E(t(\vec{x}) \cdot t(\vec{x} + \vec{p})) - E(t(\vec{x}))E(t(\vec{x} + \vec{p}))}{\sqrt{E(t(\vec{x})^2) - E(t(\vec{x}))^2}\ \sqrt{E(t(\vec{x} + \vec{p})^2) - E(t(\vec{x} + \vec{p}))^2}}$$

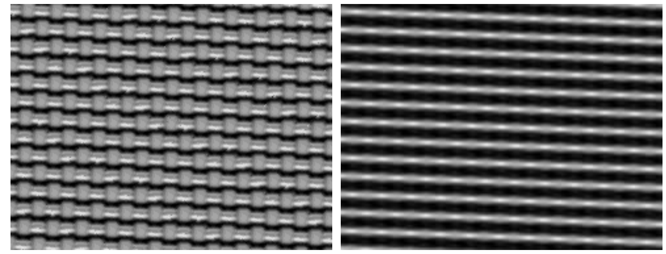

Fig. 1. Original texture image and its autocorrelation matrix

where $E(\cdot)$ denotes the expected value, that is for discrete functions the mean value.

For a texture image t of dimensions $w \times h$ the translation vector $\vec{p}$ takes all possible values from $-w/2$ to $w/2$ in x-direction, resp. $-h/2$ to $h/2$ in y-direction. This way, AM becomes a $w \times h$ matrix containing the autocorrelation values for all possible discrete translations of the texture to itself. Note that effectively one needs to compute only one quadrant of the matrix because of its symmetry. If the corresponding translation $\vec{p}$ is close to a translational symmetry, that is, if the translated texture is almost identical to the original texture, then the autocorrelation becomes locally maximal in the matrix entry of AM. Thus candidates for the two directions of periodicity are all local maxima of the matrix AM. Figure 1 shows a texture scan and its associated autocorrelation matrix. One can clearly see that the distribution of the local maxima resembles the positions of possible primitive tiles.

For an ideal texture these local maxima are evenly distributed and clearly defined against their surrounding. Unfortunately this is not true for photographs of real textures, generated from textiles. Due to distortions we get sub-maxima close to the maxima representing the directions we are looking for. To extract the two directions one has to apply some kind of optimisation strategy. Handley [7] suggests using least square optimisation for finding two vectors that best resemble all the local maxima. We implemented a different approach by first identifying the most promising directions for the two vectors and then making a best guess for their lengths.

The two directions can be calculated using either Hough transforms (see for example [13]) or a method using the mean concentration in a specific direction (first implemented in [6]). The length of a periodicity vector $\vec{p}$ is calculated by projecting the AM to a line orthogonal to the selected direction $\vec{d}$. The 2D grid of points is transformed to a multiset of numbers in 1D, say $P = \{x_1, \ldots, x_n\}$. If we projected along a periodicity direction the numbers should be densely clustered, while projecting in other directions distribute the points more loosely (see Figure 2). We can find out about the degree of clustering by computing the *mean concentration* of

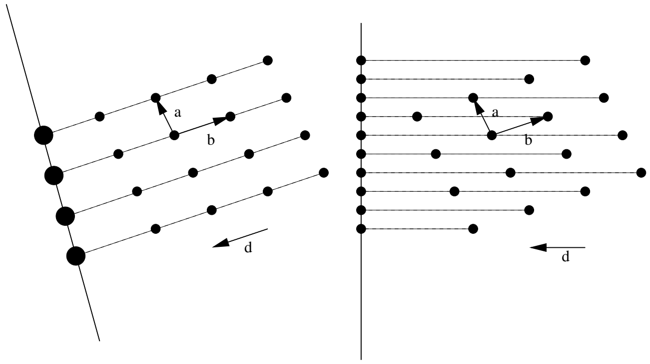

Fig. 2. Projecting a grid along d

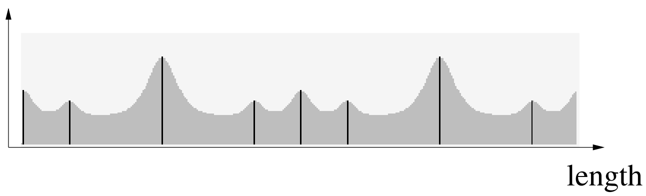

Fig. 3. typical length histogram

the multiset P given by

$$c_P := \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} e^{-\lambda \|x_i - x_j\|}$$

c_P depends only on the direction $\vec{d}$ of projection. λ must be adjusted by the user for the algorithm to work properly. By searching the biggest two maxima in $c_P(\vec{d})$ we can find best candidates for for the periodicity directions. Now we can go on and project the grid along $\vec{d_1}$ to a line in direction $\vec{d_2}$, generating a length histogram. It is useful to substitute each point of the grid by a small Gaussian bell curve to obtain a smoother histogram. Figure 3 shows a typical length histogram. The (first) global maximum tells us the length of $\vec{d_2}$. The same technique with the roles of $\vec{d_1}$ and $\vec{d_2}$ interchanged can be used to obtain the length of $\vec{d_1}$. Figure 4 shows the maxima of the AM from Figure 1 and the two best matching directions extracted using Hough transform.

Having found both periodicity vectors $\vec{p_1}$ and $\vec{p_2}$ we can obtain the primitive by averaging the entire texture modulo these vectors. This yields a parallelogram capturing just the strongly ordered aspects of the texture. Figure 5 shows the extracted primitive tile and a texture generated by repeating this tile.

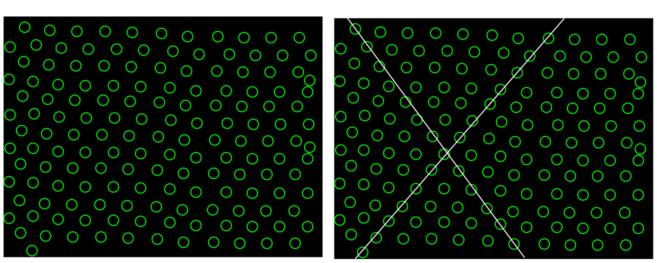

Fig. 4. Extracted maxima of the AM and best directions from Hough transform

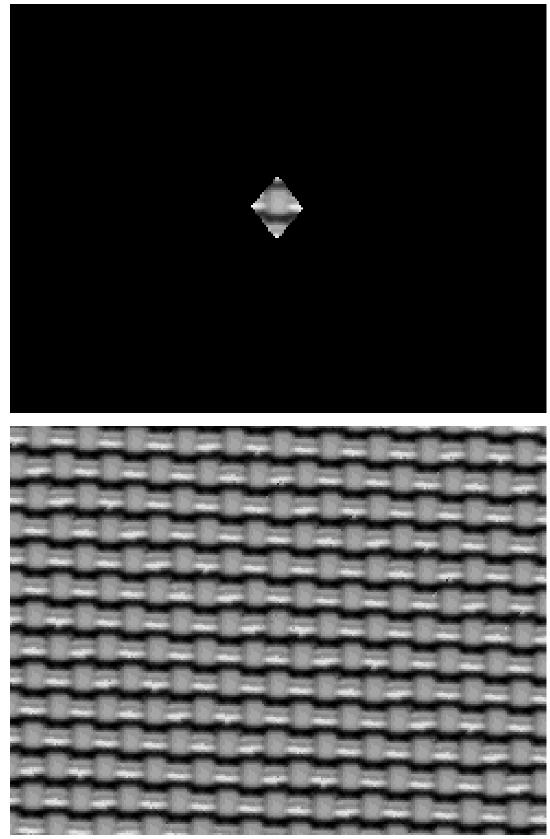

Fig. 5. Extracted primitive tile (top) and synthesised texture (bottom)

B. *Shape from Shading*

We used the algorithm of Tsai and Shah [14] to generate a height map from the 2D texture primitive. The authors state that the algorithm is ideal for setups where one has only one image and the texture is illuminated by a light source relatively close to the surface. Furthermore the image should not contain too much noise. These requirements are met in our case since we obtained the textile images using a flatbed scanner, and we removed the noise during the averaging process while extracting the primitive. Figure 6 shows a 3D model of the fabric shown in Figure 1 generated using this method.

V. Haptic Rendering

In section IV we have gathered a 3D shape model of the textile surface. In order to generate a tactile sensation from this model we need to render the information using a haptic device.

There is a variety of haptic and tactile devices available. One of the first commercially available peripherals for haptic interaction was the Phantom device by Sensable Technologies. It consists of a pen attached to a freely movable arm. The arm is equipped with sensors to capture the motion of the pen, and motors to induce resistance against such motions. A

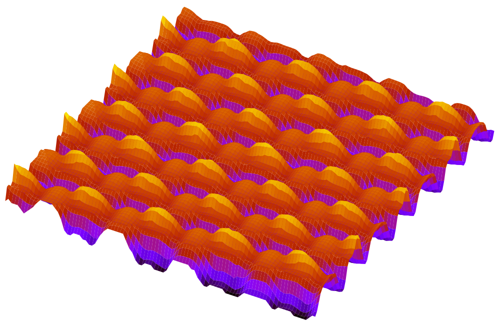

Fig. 6. 3D model of the fabric

computer can calculate feedback forces just strong enough to give the user the impression of more or less solid obstacles the pen is pressed against.

The Phantom device can be programmed using high level developer's kits (see [15], [16]). To simulate a surface, these SDKs support a collision detection. When the tip of the pen penetrates the virtual surface a penalty force is calculated, pressing the pen in a direction orthogonal to the surface. The penalty force is gained from a spring damper model as described in [15]. This way, the tip of the pen roughly follows the virtual surface while being moved giving the user a tactile impression of the textile characteristics.

VI. Comparison with Kawabata measurements

To get an impression of the performance of our method we arranged a series of experiments in which we also compared our technique with the method of Kawabata measurements by Huang [3]. Both methods create a height profile which is then used to render the information using a haptic device as described in the previous section. Since we wanted to find out more about discriminability, we chose a subset of relatively similar fabrics from [17]. Furthermore, for our experiments the haptic properties of the fabrics had to be visible in order to be reconstructable from an optical scan. These criteria resulted in a test set of the cloth samples 8, 9, 18, 22, 23, 28, 29 from [17].

To compare both methods with each other, and to compare them with real fabrics, a setup similar to [18] was chosen. In an odd-man-out forced-choice procedure three objects are presented to the subject, with two of them being identical. The subject has to tell, which one of the three objects is different from the two other ones. After that, the subject has to judge, if it was "easy", "normal" or "hard" to make a decision.
Since each odd-man-out experiment incorporates two different textiles, each subject had to answer $n(n-1)/2$ questions for n samples.

In order to understand which properties of the fabrics are important for the discrimination task a multidimensional scaling (MDS) procedure was employed. To gather the perceptual dimensions subjective distances between the fabrics had to be found. In [18] the subjective distances were computed as Craven distances (see [19]). Our approach was a little different: each answer was weighted with 1, 0.5 resp. 0.1 if the test was considered "easy", "normal" resp. "hard". If the answer was wrong, that means the subject did not identify the odd sample, the answer received weight 0. Note that the choice of weights is more or less arbitrary here. Obviously we had to choose a non-zero value for the "hard" value but this could have been a lesser value than 0.1 also. Aside from that choosing other values results in a slight transformation of the resulting spaces. But the overall qualitative distances should be kept as long as the "normal" value is located near the middle between "hard" and "easy". The subjective distance is then defined as the sum of all weights. The distances between all samples build up a complete distance graph which is then embedded into a low-dimensional space. This projection is of course subject to an error which depends on the dimension of the embedding space. The dimension is chosen as maximal in a sense that higher dimensions do not reduce the error significantly.

Twelve subjects (4 female, 8 male) participated in the experiments. They were aged between 20 and 64 years (on average 32 years). None of the subjects used the Phantom device or participated in a similar experiment before. During the tests the subjects could neither see the fabric nor hear the noises generated by the pen or the Phantom device, so that visual and acoustic impressions could not interfere with the tactile sensation.

In the first experiment the subjects could freely move a real pen (resembling the interface pen of the Phantom device) over a sample of real fabric. Figure 7 shows an MDS plot of the subjective distances gathered from the first experiment. In contrast to Figure 7 Figure 8 shows the fabrics in an objective parameter space (with values taken from [1] and [17]). As one can see the relative positions of the fabrics are quite similar in both figures, with the exception of sample 29. Thus the first dimension of Figure 7 probably resembles the roughness of the fabric as also stated in [1]. The second dimension probably corresponds to the compressional resilience.

In the second experiment the subject could explore a virtual sample of fabric generated from the optical method rendered by the Phantom device. Just like in the first experiment the size of the virtual samples was 2 cm^2. Figure 9 shows an MDS plot of the subjective distances gathered from the second experiment. Note that the MDS method has reduced the data set to one dimension here using Kruskal's "elbow"

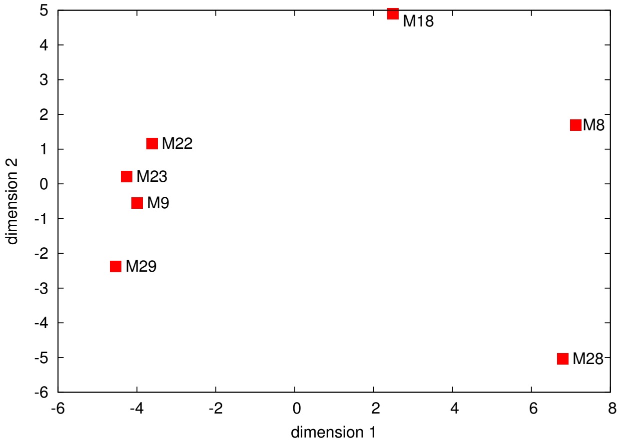

Fig. 7. MDS plot of the first experiment

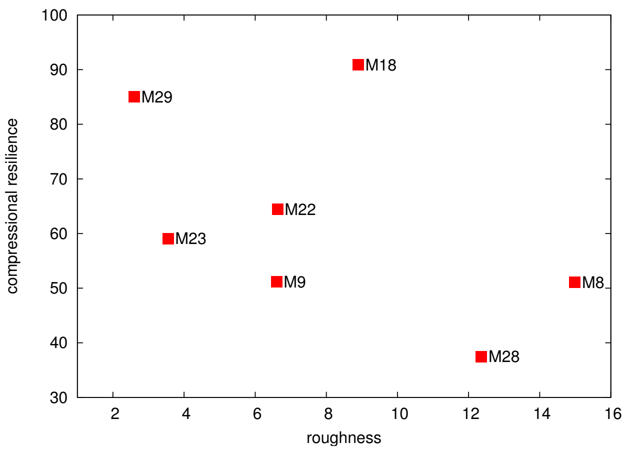

Fig. 8. Roughness and compressional resilience of the fabrics.

criterion [20]. Similar to one of the dimensions in the first experiment the one dimension that is left after reducing gives a good approximation of the textures roughness. Just like in the real world setup the samples M8 and M28 are very close to each other, resembling the real impression.

The third experiment was identical to the second, except that the haptic sensation was generated using the Kawabata measurements. Figure 10 shows an MDS plot of the subjective distances gathered from the third experiment. Just like the optical method the Kawabata method gives a good discrimination of the fabrics' roughness. There is only one exception concerning samples M8 and M28, that were very

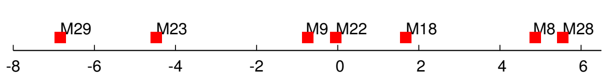

Fig. 9. MDS plot of the second experiment

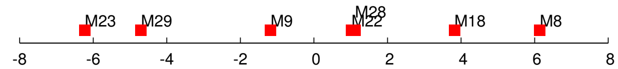

Fig. 10. MDS plot of the third experiment

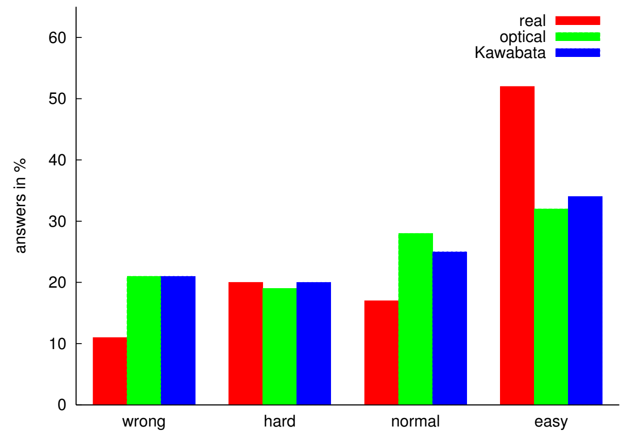

Fig. 11. Classification of discriminability

similar in the first two experiments but are placed at distant positions by the Kawabata measurements. This could possibly be caused by interpolation problems of the very fine grained surfaces of these fabrics.

During these odd-man-out tests the subjects were asked if they found the discriminability of the samples "hard", "normal" or "easy". In Figure 11 one can see the accumulated results of these questions. One observes that it seems to be much easier and more accurate to tell the different fabrics apart in the real setup. The two virtual methods perform relatively similar with no significant drawbacks on both sides.

In Figure 12 the errors of the subjects are shown for each fabric. We see that our method performs comparable to Huang's method with the only — already known — exception of M8. One can see in Figure 12 that the errors for the samples M18, M28 and M8 are very low for the experiment with real fabrics. This is probably due to their relatively high distance in the second perceptual dimension mentioned earlier in this section (see Figure 7).

VII. Conclusion

We have presented an automatic method to generate tactile representations of fabrics from optical scans. This way one can render a tactile sensation of virtual cloth using very inexpensive hardware like optical scanners. We have shown that our method performs similar to the well known technique of Kawabata measurements. However, more extensive test should be carried out in order to show advantages and disadvantages of our method.

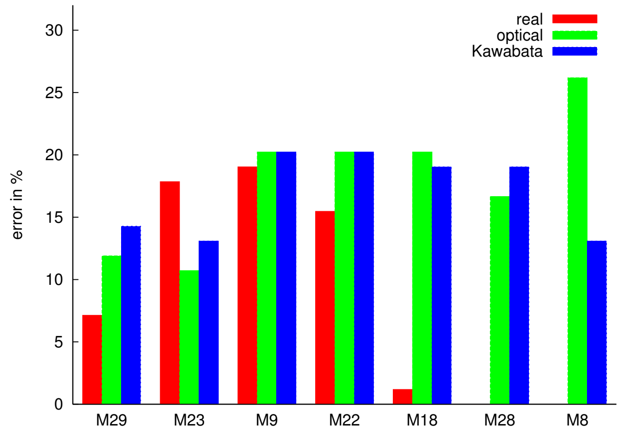

Fig. 12. Errors of the subjects.

From our experiments we conclude that the main influence on the discriminability of different samples of cloth are roughness and compressional resilience (”softness”). A consequence of these experiments is, that a user can not easily detect symmetries in the fabric patterns, because otherwise our method should have shown significant advantages over the Kawabata method.

We could not yet identify more features apart from roughness and compressional resilience that had any notable influence on the tactile discrimination of the patterns. Further experiments should be considered to gain more insight in other features of a fabric. More haptic features that might influence the haptic perception of textiles can be found in [21].

So far we have tested our method only with the described haptical device. There is a variety of other haptic devices available, for example, tactile arrays [22] or data gloves, some of which are better suited for fine detailed tactile sensations. It is not clear how many of the tactile characteristics of a fabric can be expressed using a pen-like device. This opens the field for better haptic displays that should be investigated together with the presented method, for example with a special vibrotactile display in [22]. In order to gain more insight in the applicability of the method described it should be tested with other haptical devices also.

Acknowledgment

The project ”HAPtic sensing of virtual TEXtile” (HAPTEX) is a research project funded under the Sixth Framework Programme (FP6) of the European Union (Contract No. IST-6549). The funding is provided by the Future and Emerging Technologies (FET) Programme, which is part of the Information Society Technologies (IST) programme and focuses on novel and emerging scientific ideas. Its mission is to promote research that is of a long-term nature or involves particularly high risks, compensated by the potential of a significant societal or industrial impact.

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