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WAVELET SUPERRESOLUTION AND QUASI-SUPERRESOLUTION IN ROBOT VISION

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ABSTRACT
This article presents results of image enhancement for robot vision. Results are obtained by superresolution techniques in wavelet domain. The calculated motion of wavelet coefficients in stationary image can enhance image quality. It can be used as interpolation information for increasing resolution. This is basis for wavelet quasi-superresolution, where one low-resolution image is interpolated to high-resolution grid. Motion field of wavelet coefficients can be possibly used to predict position of image features in the next frame in multiframe approach too. Interpolation of wavelet coefficients of the first generation in combination with motion field produces weight functions. The weight functions are intuitively introduced the second generation wavelets. If this is combined with the morphology operations, the result is the third generation wavelets on the first generation settings.
Keywords: wavelet superresolution, robot vision, quasi-superresolution, intuitive SGW

1. INTRODUCTION
Digital image and video processing play important role in many robot operations, such as avoiding obstacles, object recognition, measurement, etc [1, 2]. Superresolution is process of obtaining higher resolution image from several low resolution images, called frames in image sequences. To enhance resolution of robot vision algorithms, it is possible to use superresolution algorithms. Superresolution problem includes motion estimation interesting in robotics. It also includes restoration problem. Restoration problem can be solved as in quasi-superresolution [3].
Quasi-superresolution algorithm is suitable for calibration. Smaller length units can be used if we obtain higher resolution (more pixels for same size of images). That leads to more precise data for robot manipulation. However, it decreases on-line performance due to large amount of data necessary for these operations.
Superresolution is suitable for analysis of movement, tracking and automatic recognition of similar objects. Higher resolutions are very important in self-guided autonomous vehicles, such as submarine underwater vehicles, but also in i.e. robot supplement for bartender and similar operations. Higher resolution can make more precise many operations and actions.
There are different types of superresolution, but there can be grouped into four classes: single-input-single-output (SISO), single-input-multiple-output (SIMO), multiple-input-single-output (MISO), and multiple-input-multiple-output (MIMO) [4]. Two cases are investigated: quasi-superresolution (SISO case) and motion estimation problem (MIMO case).

2. MOTION ESTIMATION IN SUPERRESOLUTION

The estimation of motion in image sequence is the first step in robot vision. Motion estimation has a central role in multiframe superresolution restoration. The motion of objects 3-D space may be described by a 3-D velocity field. Its projection to 2-D image plane is projected motion or the 2-D motion field [4]. The spatiotemporal variation at the focal plane results from the interaction of the scene illumination with the objects in the scene, motion of the objects in the scene and changes of camera parameters (position, orientation, focal length, focus setting). Camera records resulting intensity variation projected at the focal plane. Intensity variation of pixels in time carries information about the projected motion, but it does not corresponds to 2-D velocity field.

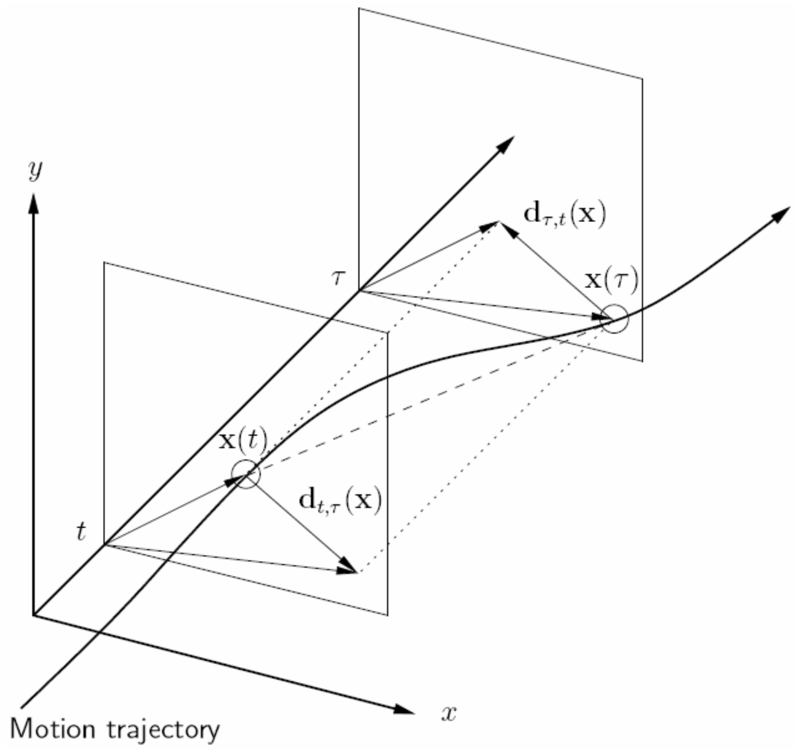


Figure 1. Motion estimation problem

Consider a point $X(t) = [X(t), Y(t)\ Z(t)]^T$ on a moving object in 3-D space. At time t, the camera system projects the 3-D point X(t) onto the camera focal plane at position $x(t) = [x(t), y(t)]^T$. Given two time instants t, τ with $t < \tau$ and corresponding image intensities $f_t(x)$ and $f_\tau(x)$, the position of the projection of the 3-D point on the image plane at time t, given by x(t), may be related with its position at time τ, given by $x(\tau)$, in two ways (see Figure 1):

– The forward motion,

$$d_{t,\tau}(x) = x(\tau) - x(t) \tag{1}$$

describes the displacement in the image plane of the projected 3-D point from time t to time τ. The forward motion estimate $d_{t,\tau}(x)$ may be used for backward prediction where image values are predicted from a future reference frame using

$$f_t(x) = f_\tau(x + d_{t,\tau}(x)) \tag{2}$$

– The backward motion

$$d_{\tau,t}(x) = x(t) - x(\tau) \tag{3}$$

describes the displacement in the image plane of the projected 3-D point from time τ to time t. The backward motion estimate $d_{\tau,t}(x)$ may be used for forward prediction where image values are predicted from a past reference frame using:

$$f_\tau(x) = f_t(x + d_{\tau,t}(x)) \quad (4)$$

3. QUASI-SUPERRESOLUTION AND CALIBRATION OF ROBOTS' CAMERAS

Let $M(x_m, y_m, z_m)$ is spatial position of arbitrary point with respect to the camera reference frame S_C. Let $m_M = [u\ v]$ is the projection of that point to the image plane. The relationship between M and m_M is given with [5]:

$$s[m_M\ 1]^T = P\ [M\ 1]^T \quad (5)$$

where $P \in R^{3x4}$ is the perspective projection matrix of the camera obtained by camera calibration and s is a scaling factor defining the position of the point M on the optical ray. All the images are made up of a rectangular array of small square or rectangular elements called pixels (abbreviation of picture elements). Each pixel has an associated image intensity value. I.e. in CT 512x512 pixels, each pixel corresponds to an element of the cut through patient of about 0.5x0.5 [mm^2]. In 3D imaging, each picture element corresponds to a small volume and it is called voxel. In CT example dimensions are 0.5x0.5x1.5 [mm^3] [6].

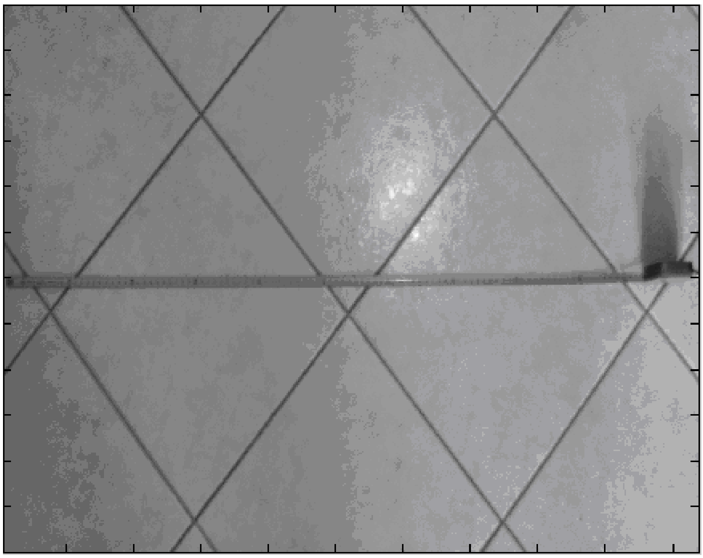
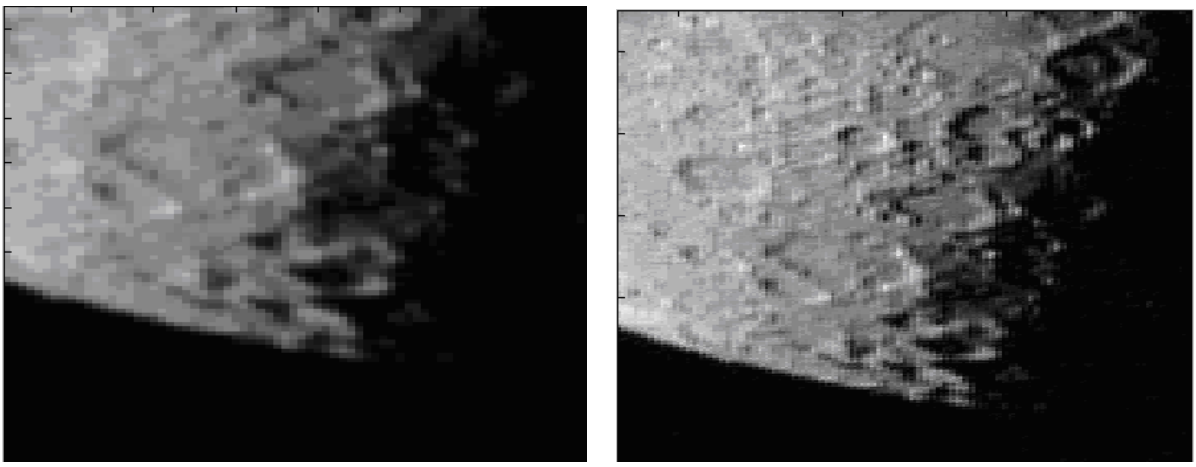
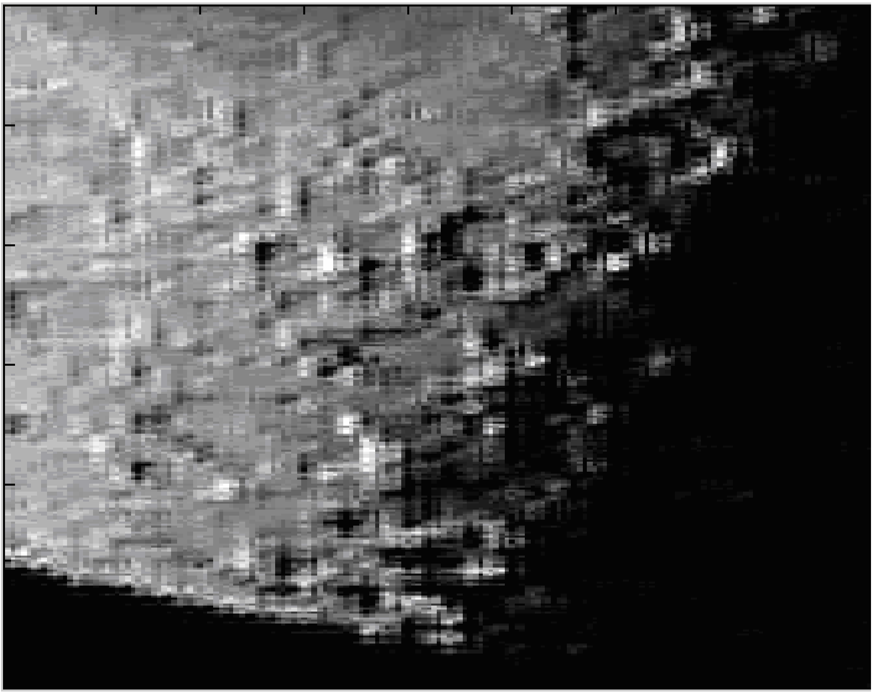


Figure 2. Measurement: 1 meter length vs. number of pixels can be used to measure any distance



a) b)



c)

Figure 3. Motion field superresolution: a) zoomed part of the original image, b),c) zoomed part of the motion field processed image with and without wavelets

To establish natural dimensions, which correspond to pixel or voxel in robotics, we need to get calibration measurement. In sections 2 and 3, we used the first generation wavelets as basis for creation of the second generation wavelets, which are implemented in various applications [7].

4. CONCLUSIONS

Unfortunately, this entire interesting research and complete reference list can not be presented due to limited space available, so the paper should be understood as an extended abstract. There was not space to present used algorithms and wavelets, as well as filters. The second generation wavelets created from the first generation (as used here) we call intuitive wavelets, because of intuitive way of introducing differences in motion field and weight functions.

An interesting approach is to introduce the second generation wavelets on the first generation settings. Unfortunately, there was not enough space to explain this approach.

Results presented in section 3 are promising for future research. Further research should include morphology and color images for segmentation and feature extraction. Motion field can be exploited for prediction of feature movements.

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