A hybrid spatiotemporal and Hough-based motion estimation approach applied to magnetic resonance cardiac images

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ABSTRACT

Myocardial motion analysis and quantification is of utmost importance for analyzing contractile heart abnormalities and it can be a symptom of a coronary artery disease. A fundamental problem in processing sequences of images is the computation of the optical flow, which is an approximation to the real image motion. This paper presents a new algorithm for optical flow estimation based on a spatiotemporal-frequency (STF) approach, more specifically on the computation of the Wigner-Ville distribution (WVD) and the Hough Transform (HT) of the motion sequences. The later is a well-known line and shape detection method very robust against incomplete data and noise. The rationale of using the HT in this context is because it provides a value of the displacement field from the STF representation. In addition, a probabilistic approach based on Gaussian mixtures has been implemented in order to improve the accuracy of the motion detection. Experimental results in synthetic sequences are compared with an implementation of the variational technique for local and global motion estimation, where it is shown that the results are accurate and robust to noise degradations. Results obtained in real cardiac magnetic resonance images are presented.

Keywords: Motion estimation, optical flow, time-frequency representations, Hough Transform, Wigner Distribution,

1. INTRODUCTION

Motion estimation is a key problem for the analysis of image sequences. Visual images and the dynamic evolutions of those images provide enormous amounts of information about our surrounding environment. By observing changes in a scene over time, 3D scene properties and motion parameters can be obtained. We can discover the three-dimensional structure of the scene, make predictions about collisions, and infer material properties of objects, such as their stiffness and transparency. Much of this information is revealed by the motion of the different parts of the scene.

Because of the richness of motion as an information source, analysis of visual motion is essential for many practical applications. These range from image-processing problems such as efficient coding or enhancement of motion pictures, to passive machine vision problems such as determining the shape of a moving object or recovering the motion of the camera relative to the scene, to active perception applications in which an autonomous agent must explore its environment [1]. It is also useful for performing motion segmentation; for computing the focus of expansion and time-to-collision; for performing motion-compensation image encoding and for measuring blood flow and heart-wall motion in medical imagery.

The analysis of heart wall deformation has important clinical implications for the assessment of viability of the heart wall and provides quantitative estimates of the location and extent of ischemic myocardial injury. Quantifying the extent of regional wall motion abnormality can aid in determining the myocardial effects of coronary artery diseases. Among all available imaging methods, Cardiac Magnetic Resonance imaging (CMR) is recognized as the best imaging method for the dynamic exploration of the cardiac function, and it is used not only for the scientific purpose of understanding heart motion but also for the clinical need to diagnose heart disease.

However, the estimation of optical flow is a challenging problem in this kind of image analysis because of a wide range of possible motions and presence of noise. In addition to this, the non-rigid motion of the heart makes cardiac motion estimation a complex problem.

In this paper, an algorithm for computation the optical flow applied to CMR based on the computation of the Wigner-Ville distribution and the Hough Transform is presented. The paper is organized as follows. Section 2 briefly reviews the problem of computing optical flow and explains the frequency-based methods. Section 3 provides an explanation of the new algorithm proposed. Section 4 evaluates the method with synthetic and real images and compares it with a variational approach and Section 5 concludes the paper.

2. OPTICAL FLOW ESTIMATION

From the information available from a sequence of images, it is only possible to derive an estimate of the motion field, which is called optical flow. Although optical flow is generally not equivalent to the true motion field, it is quite similar in most of the cases.

Numerous theoretical and practical studies on the optical flow estimation from image sequences and on the useful information it contains have been performed. Despite this wide variety of approaches, algorithms for computing optical flow are usually divided into three categories [1]:

- Differential techniques: also known as “gradient” techniques, these estimate optical flow vectors from the derivatives of image intensity over space and time. These are typically derived directly by considering the total temporal derivative of a ’preserved’ quantity such as the brightness.
- Matching techniques: these operate by matching small regions of image intensity or specific “features” from one frame to the next. The matching criterion is usually a least squares or normalized correlation measure.
- Frequency-based or filter-based techniques: these techniques are based on spatio-temporally oriented filters (i.e., velocity-sensitive), and are typically motivated and analyzed by considering the motion problem in the Fourier domain. They fall into two categories, energy-based and phase-based.

Each technique has several advantages and disadvantages. Numerical differentiation is sometimes impractical because of small temporal support or poor signal-to-noise ratio. In these cases, it is natural to consider correlation techniques. Among the advantages brought by the frequency-based methods, it is found that motion-sensitive mechanisms operating on spatiotemporally oriented energy in Fourier space can estimate motion in image signals for which matching approaches would fail [2]. One example can be the motion of random dot patterns.

The differential method has a major drawback in the estimation of the first and second derivatives of the pixel intensity, mainly in the case of noisy images. To improve noise robustness, a common strategy is to use regularization methods based on variational integrals. On the contrary, frequency-based methods are in general more robust to noise [3]. Due to the fact that cardiac images are quite noisy, a frequency-based approach has been chosen for the implementation of our algorithm

2.1 Optical flow

The initial hypothesis for measuring image motion is that the intensity structures of local time-varying image regions are approximately constant under motion for at least a short duration [4]. That is, changes in the image intensity are due only to translation of the local image intensity and not due to changes in lighting, reflectance, etc. According to this assumption, the total derivative with respect to time of the image intensity function should be zero at each position in the image and at every time.

Let $i(\bar{x},t)$ denote the intensity function, where $\bar{x}=(x,y)$ represents the pixel position and t is the time. If the intensity remains constant, then

$$i(\bar{x},t) = i(\bar{x} + \delta\bar{x}, t + \delta t) \tag{1}$$

where $\delta\bar{x}$ is the displacement of the local image region at $(\bar{x},t)$ after time δt. Expanding the left-hand side of this equation in a Taylor series yields

$$\nabla i \cdot \bar{v} + i_t = 0 \tag{2}$$

where $\nabla i = (i_x, i_y)$ is the spatial intensity gradient, i_t is the derivate of the intensity with respect to time, and $\bar{v} = (v_x, v_y)$ is the image velocity.

This equation is called the optical flow constraint equation (OFCE). Unfortunately, one scalar equation is not enough for finding both components of the velocity field. It gives only the component in the direction of the gradient, that is, the normal flow. This problem is usually called the aperture problem [5].

2.2 Frequency domain description

Many important insights about the estimation of motion may be explained in a straightforward manner by considering the problem in the Fourier domain. This is easily appreciated by considering the motion of a one-dimensional signal. We can represent such a signal as an intensity image in which the intensity of each pixel corresponds to the value of the signal at a particular location and time. A translating one-dimensional signal has the appearance of a striped pattern, where the stripes are oriented at an angle of $\alpha = \arctan(1/v)$, where v is the velocity of the signal [1]. Clearly, the Fourier decomposition of this signal is a set of sinusoids of this same orientation, and varying wave number (spatial frequency magnitude). Thus, the power spectrum of the Fourier transform will be located along a line that passes through the origin at angle α, as illustrated in figure 1.

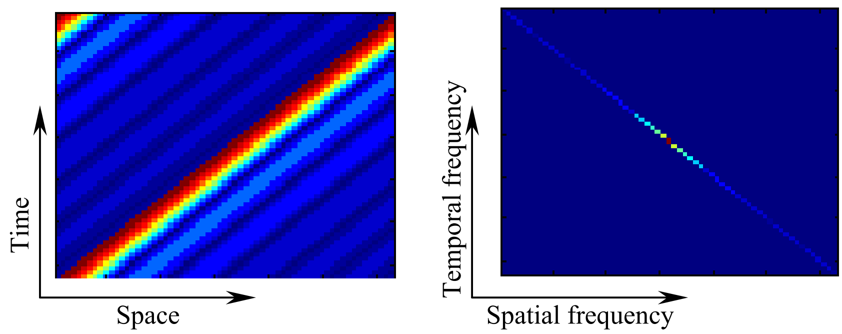


Fig. 1. a) Sinc function translating (v=1 pixel/sec). b) Fourier transform of the signal a).

The situation in two dimensions, although more difficult to illustrate, is analogous. A translating two-dimensional pattern has the appearance of oriented "bundles of fibers" in a 3D space-time (x, y, t). The Fourier transform spectrum of an image undergoing rigid translation lies in a plane in the spatio-temporal frequency domain.

For analyzing a video sequence through a three-dimensional Fourier transform let us assume again that we can represent an image sequence through a function $i_0(x, y)$ such as

$$i(x, y, t) = i_0(x - v_x t, y - v_y t) \tag{3}$$

where the main assumption here is that moving objects must move with a uniform velocity vector (v_x, v_y) and must have a constant illumination. Now, by calculating the spatial and temporal Fourier transform of the sequence $i(x, y, t)$, we obtain

$$I(f_x, f_y, f_t) = I_0(f_x, f_y)\delta(v_x f_x + v_y f_y + f_t) \tag{4}$$

where I_0 represents spatial Fourier transform of i_0 and δ is the Dirac delta function.

Thus, $I(f_x, f_y, f_t)$ is nonzero only on a plane, which is called the *motion plane* [6]. This plane passes through the frequency origin. Its equation is given by

$$v_x f_x + v_y f_y + f_t = 0 \tag{5}$$

Estimating parameters of this plane leads to estimate the velocity vector components (v_x, v_y) of the moving object. Therefore, equation (5) can also be viewed as the Fourier transform of the OFCE

$$\frac{\partial i(x,y,t)}{\partial t} + v_x \frac{\partial i(x,y,t)}{\partial x} + v_y \frac{\partial i(x,y,t)}{\partial y} = 0 \tag{6}$$

2.3 STF approach

Among the different techniques for computing optical flow using frequency-based methods, the spatiotemporal-frequency approach (STF) has been proposed, which gives a simultaneous representation of a signal in space and spatial frequency variables [7]. One implementation of the STF approach employs the Wigner-Ville distribution (WVD) as an underlying STF image representation.

The major motivation for considering the use of STF image representation approach as a basis for computing optical flow comes from the literature on mammalian vision. In particular, some investigations have demonstrated that many neurons in various cortical areas of the brain behave as spatiotemporal-frequency bandpass filters [8]. In the field of non-stationary signal analysis, the WVD has been used for the representation of speech and image. Jacobson and Wechsler [7,9] were the first to suggest the use of the WVD for the optical flow estimation.

The Wigner Distribution was introduced by Wigner as a phase space representation in Quantum Mechanics, and it gives a simultaneous representation of a signal in space and spatial frequency variables [10]. Later, in the area of signal processing, Ville derived the same distribution that Wigner proposed several years before [11]. The WVD can be considered as a particular occurrence of a complex spectrogram in which the shifting window function is the function itself [12].

The WVD distribution of a moving sequence is a 6-dimensional function defined by

$$W_i(x, y, t, w_x, w_y, w_t) = \oiiint R_i(x, y, t, \alpha, \beta, \tau) e^{-j(\alpha w_x + \beta w_y + \tau w_t)} d\alpha d\beta d\tau \tag{7}$$

where

$$R_i(x, y, t, \alpha, \beta, \tau) = i(x+\alpha, y+\beta, t+\tau) i^*(x-\alpha, y-\beta, t-\tau) \tag{8}$$

and where * denotes complex conjugation.

Again, for the case where a time-varying image $i(x,y,t)$ is uniformly translating at some constant velocity, the WVD of this image is

$$W_i(x, y, t, w_x, w_y, w_t) = \delta(v_x w_x + v_y w_y + w_t) W_i(x - v_x t, y - v_y t, w_x, w_y) \tag{9}$$

From (9), the WVD of a linearly translating image with velocity (v_x, v_y) is everywhere zero except in the plane defined by

$$\{(x, y, t, w_x, w_y, w_t) : v_x w_x + v_y w_y + w_t = 0\} \tag{10}$$

Equivalently, for an arbitrary pixel at x, y, t, each local STF spectrum of the WVD is zero everywhere except on the plane defined in (10). For this reason, if a procedure for estimating the velocity associated with a given STF spectrum is found, we will obtain a space and time varying optical flow function. In the next sections we will describe how the Hough Transform can be used for computing the optical flow together with the WVD.

3. IMPLEMENTATION ISSUES

In section 2 details about the frequency description on motion estimation, specifically on a spatio-temporal approach, have been presented. In this section, this background is used to make a description about the method proposed. As mentioned before, it is necessary to choose a procedure for estimating the slope of the plane found in the spectrum. In our algorithm, the technique proposed is the HT due to the ability to discard outliers induced by the WVD. In the next section, a short explanation of the HT is made, followed by the description of the algorithm proposed.

3.1 Hough Transform

The problem of determining the location and orientation of straight lines in images is of great importance in the fields of computer vision and image processing. One approach used for the detection of lines is the Hough Transform (HT), a nonlinear filtering technique to estimate the position and direction of certain curves in a discrete image [13]. Despite its name, it is not an invertible transform in the sense of Fourier transform or the like. Another pose estimation method commonly used is the least squares (LS) algorithm, which is based on the minimization of an objective function: the sum of squared distances between image features and the model. The HT is the classical approach for finding the parameters of lines in a binary image, and maps each image point to all points in the parameter space, which could have possibly produced the image point. Thus, each image point votes for the shape parameters that could have produced it. The points in the parameter space that accumulate the greatest number of votes, which appear as peaks, are the most likely to have produced the shapes in the true image. Therefore, the HT reduces the problem of detecting spatially spread patterns in the image space to that of finding localized peaks in a dual parameter space [14]. Its main advantages are the ability to discard features belonging to other objects and the robustness against incomplete data and noise [15]. These characteristics are very important in our problem due to the fact of the presence of cross-terms of the Wigner-Ville distribution, so we can use a more efficient method for determining the motion plane.

The parameterization specifies a straight line by the angle θ of its normal and its perpendicular distance ρ from the origin. If we restrict θ to the interval $[0, \pi]$, then the normal parameters for a line are unique. With this restriction, every line in the x-y plane corresponds to a unique point in the θ-ρ plane [16].

3.2 Algorithm proposed

As seen in the previous section, a line can be completely characterized in the Hough plane, as well as a line and also a plane. This feature has been used to determine the velocity by means of the HT applied to the STF spectrum.

Our first approach was based on the use of the HT on the whole spectrum in order to find the plane. In this way, each pixel of the spectrum with a nonzero value was represented in the Hough plane. However, those pixels of the WVD belonging to cross-terms influenced on the final result, and sometimes can produce incorrect solutions. For this reason, we have used another approach based on the HT computation for each of the frames of the spectrum in order to detect a line on each of them and in this way discarding the information from cross-terms pixels. Furthermore, this implementation is computationally less demanding.

At the end, our problem can be reduced to find one straight line in each temporal frame. Furthermore, we already know that the spectrum contains the frequency origin, and we can observe that the lines in different temporal frames are parallel. Taking into account these facts and by means of applying the HT the plane will be detected.

We will illustrate our algorithm with an example. Given a sequence composed of a circular object moving with a oblique velocity in the coordinates X and Y, performing the WVD we will find a plane which is represented in each temporal-frequency frame by a line. Some of these frames are shown in Figure 2.

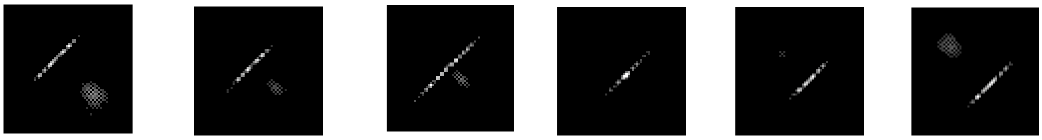


Fig. 2. Several frames of the WVD of the sequence

With our method, we perform the HT for each of the frame of the spectrum (represented in Fig. 2). The result of the HT applied to the first three frames is shown in Fig. 3, where the maximum point of each HT gives the position of the line by means of θ and ρ.

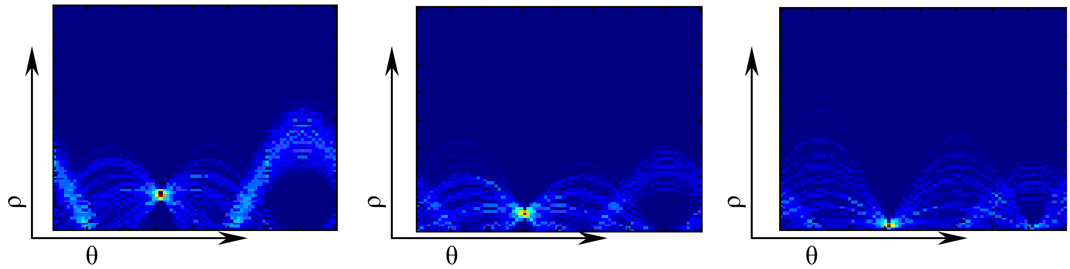


Fig. 3. HT of the first three frames shown in Fig. 2.

Taking the maximum value of this HT, the information of the position for each line is provided. As every straight line found in one frame is parallel to the others, the maxima found in all the HT lie all in a line, which means that every line of the spectrum has the same angle θ. Summing up all the HT transform of the frames of the spectrum, it is easily found that all these maxima belong to one line (see Fig.4-a).

Actually, the information provided by the angle of one of the peaks would be enough for estimating the direction of the velocity. But most of the times, ideal conditions are not met (we must remember, for example, the presence of cross-terms induced by the WVD), and in some cases, by considering only one of the frames we can end up with an erroneous solution, due to noise or other external factors. We propose to use the redundant information of all the frames and the property shown in the Fig. 4-b), which is that all the maxima form a straight line and by applying the HT to the summation of all the peaks, erroneous peaks can be easily discarded.

In order to estimate the magnitude of the velocity, the values of the different ρ obtained have been used (i.e. the distance from the lines to the origin), so as to estimate the slope of the plane. As Fig. 4-b shows, the values of ρ lie along a line, whose slope can be measured by means of another HT.

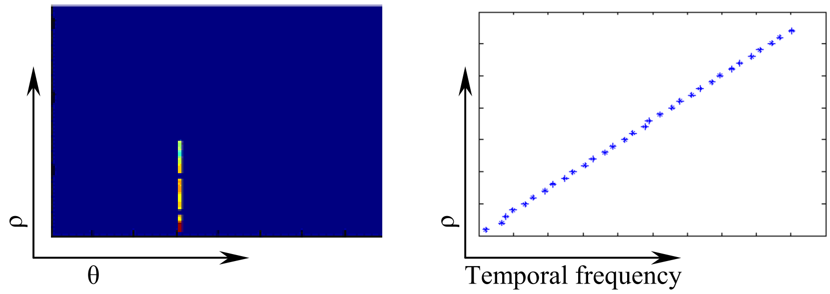


Fig. 4. a) Summation of all maxima of the HT of all the frames of the WVD. b) Values of ρ of the HT for the different frames of the WVD

3.3 Implementation of the algorithm for local estimation of motion

This implementation should be used when the *a priori* information of assuming only one object in the sequence is unknown. Thus, a small window is assigned to each pixel of the sequence, and the algorithm presented in the previous section is executed for each of the windows. However, using only one fixed size of window can lead to several problems such as aliasing effects. For this reason, the technique above described has been modified in a hierarchical coarse-to-fine framework.

A hierarchical scheme allows the images to be decomposed in different scales of resolution in the form of Gaussian or Laplacian pyramids. Because of a low-frequency representation at coarser resolutions, the optical flow constraint equation becomes applicable in the case of large image motions. In addition to handling fast motions, hierarchical processing also offers increased computational efficiency [2]. With only one scale of resolution, because of low sampling rates and aliasing effects, the OFCE becomes inappropriate.

In the case of our implementation, the problems which have being solved with the hierarchical implementation are the aliasing effect, the apperture efect and the problem of measuring large or too small image motions. Considering again the example shown in Fig. 1, let us suppose a decrease in the velocity to 0.5 pixels per second (see Fig. 5-a). Its spectrum is shown in Fig. 5-b), where the aliasing is clearly visible. With a coarse resolution in space, taking only one pixel out of two, the velocity is increased a factor of two (Fig.5-c), and consequently, the aliasing is eliminated (Fig. 5-d). With this hierarchical implementation, the most accurate velocity is chosen after having obtained the results for all the scales of resolution. The decision about the velocity measurement is made taking into account the accuracy of the HT.

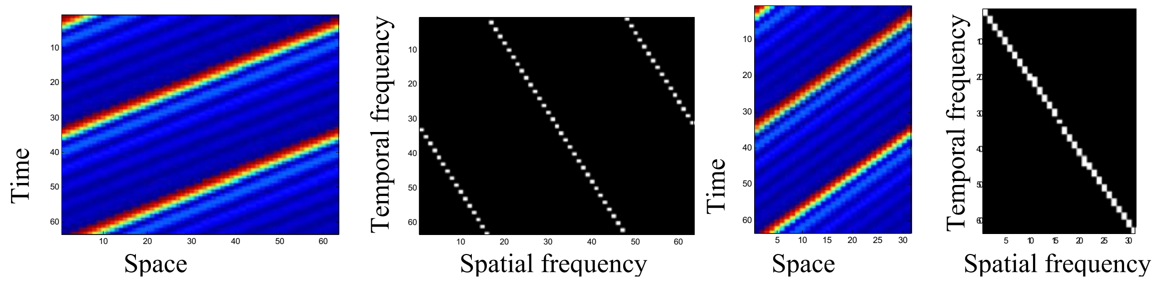


Fig. 5. a) Sinc function translating (v=0.5 pixel/sec). b) Spectrum of the signal. c) Signal downsampled in space. d) Spectrum of the signal c).

4. RESULTS

4.1 Results under synthetic sequences

The new methodology proposed here was applied for evaluation purposes to synthetic images of a moving circular object with constant intensity, which can be described as:

$$\begin{cases} x(t) = \rho \cdot \cos(\theta) + x_0 + t \cdot v_x \\ y(t) = \rho \cdot \sin(\theta) + y_0 + t \cdot v_y \end{cases} \tag{15}$$

where ρ represents the radius of the circle with a constant gray level, θ varies from 0 to 2π, $[x_0, y_0]$ is the initial point, t corresponds to the variation of the position with the time and finally, v_x and v_y are the velocity components of the circle. Fig. 8 shows three images of the sequence, for v_x =1 and v_x =-1.

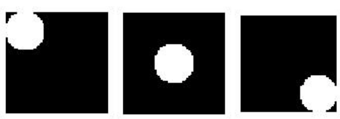


Fig. 6. Images of the synthetic sequence for $v_x = 1$ and $v_y = -1$

In order to estimate the global motion, we have obtained a smoothed 3D frequency spectrum by means of a Hanning filter which has been previously introduced [3].

The method was applied to distinct values of ρ, $[x_0, y_0]$ and $[v_x, v_y]$. Some results are shown on Table 1. For these simple sequences, when we consider a moving object with a uniform velocity and we calculate a global motion, an accurate information about the optical flow can be obtained by means of the method based on WVD-HT.

Table 1. Translations in pixels/frame for several examples.

Actual translation		*Estimated translation*	
V_x	V_y	v_x	v_y
1	0	1.0000	-9.4941e-016
1	-1	0.9717	-0.9748
-0.7	0.5	-0.6773	0.5203
0.7	-1	0.6935	-0.9434
-1.2	-0.7	-1.1973	-0.6790

A further step on the analysis has been done, estimating the motion locally by means of the hierarchical implementation above explained. An example with two hierarchical levels will be discussed later in Fig. 7-a, where the image size is 128x128x25 pixels, and window sizes are 25 and 50 pixels. For these sizes of window, we can observe that the optical flow estimated in the regions near to the border of the circle is very accurate (compare with the results obtained with the variational method in Fig. 7-b). Only regions inside the circle provide uncertainty due to the apperture problem, and therefore values for optical flow are less accurate.

We have applied the variational method to the same simple sequence used before. We can observe the results for an arbitrary frame obtained for v_x=1 and v_y=0 in the Fig. 7-b, where it is shown the optical flow obtained after regularization. We can see that the values of optical flow are about 1 pixel per frame, but the optical flow doesn't always fit the right positions. The uncertainty of the optical flow obtained in regions inside the circle, which is due to the apperture problem, has been partially corrected by means of the regularization.

a) 

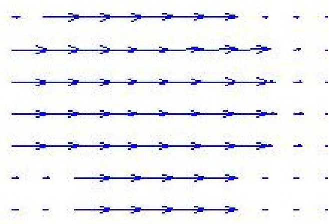
b) 

Fig. 7. a) Optical flow with local estimation using the method based on WVD-HT; b) Optical flow obtained using variational methods.

Differential methods provide an optical flow for each pixel of the sequence, so it can be a tough task to perform a direct comparison with the global motion estimation method based on WVD-HT, but we can make a comparison through the local motion estimation. Fig. 7-a and 7-b show that results obtained with our method are comparable with the variational technique and the motion field obtained with our method fits better the right positions.

Finally, to test the robustness against noise of the new algorithm proposed, several experiments have been conducted adding different types of noise to the sequence. Table 2 shows results of estimated translation for our sequence with added noise, when the actual translation is V_x = 1 pixel/frame and V_y = -1 pixel/frame. The Gaussian and Speckle added noise are characterized by its variance and the Salt & Pepper noise by its density.

Table 2. Estimated translations provided by WVD-HT method in pixels/frame for actual translation V_x=1 and V_y=-1 for different additive noise variances.

	Gaussian		*Speckle*		*Salt&Pepper*	
Noise Variance/Density	v_x	v_y	v_x	v_y	v_x	v_y
0.05	0.97	-0.97	0.97	-0.97	0.96	-0.98
0.1	0.98	-0.95	0.97	-0.97	0.96	-0.98
0.2	0.95	-0.95	0.98	-0.96	0.98	-0.97
0.4	1	0	0.97	-0.98	0	-1

In the case of the variational method, the added noise of each pixel has influence on the estimation of first and second derivatives of the pixel intensity. The optical flow obtained, obviously, gets worse as the noise increases.

4.2 Motion estimation for CMR sequences

The method proposed has been applied to real CMR sequences in order to estimate the myocardial deformation, and its performance has been evaluated under these non ideal cases. A local analysis of motion has been carried out, asigning a small window to each pixel of the sequence, and executing the algorithm for each of the windows. Thus, an optical flow for all the pixels of the sequence is obtained when the algorithm is executed for each of the pixels of the sequence.

In this case, the analysis is more complex because the initial conditions are not the ideal ones. The first condition is that objects must move under a uniform velocity. In a real sequence, a uniform velocity cannot be guaranteed. So the size of the sequence in the temporal axis must be small enough to suppose uniform movements. However, the number or images must be enough to obtain useful information on the slope of the plane contained on the 3D Wigner-Ville distribution.

On the other hand, the main problem of these sequences is the presence of a deformable cardiac wall instead of a rigid moving object. Because of this reason, some cross-terms are found in the spectrum and in some cases, these terms can mask the plane. In order to try to make uniform these small changes between the images of the sequence, a preprocessing stage has been performed, filtering and thresholding the image. Nevertheless, the problem of the presence of a deformable object is going to be the main one.

Fig. 8-a presents several frames of one of the windows of the original sequence (extracted from a cardiac magnetic resonance), where it is shown how the object doesn't preserve the form. The correlation of this sequence (Fig. 8-b), therefore, is variable with time. For that reason, as seen in Fig. 8-c, the spectrum doesn't have a clear plane detectable for the HT. This fact is due to the non-uniformity of this correlation. Thus, it is necessary to have a uniform correlation in order to obtain a better plane. A probabilistic approach based on Gaussian mixtures has been implemented. Information about the position and shape of each frame of correlation is extracted and processed so as to get a uniform correlation where the main information from the original one is preserved. Thus, the plane is detectable (Fig. 8-d) and the accuracy of the motion detection is improved.

Fig. 9 shows the results of the HT applied to the spectrum of figure 8-d. The first figure represents the summation of all the maxima of the HT. As mentioned before, almost all of them belong to the same angle and therefore, the direction of the movement is easily estimated. In the second figure are represented the values of ρ, information needed to evaluate the slope of the plane. The green line is an approximation by least squares, and the red line is the HT result. As seen, the LS gives a worse result because it doesn't eliminate outliers.

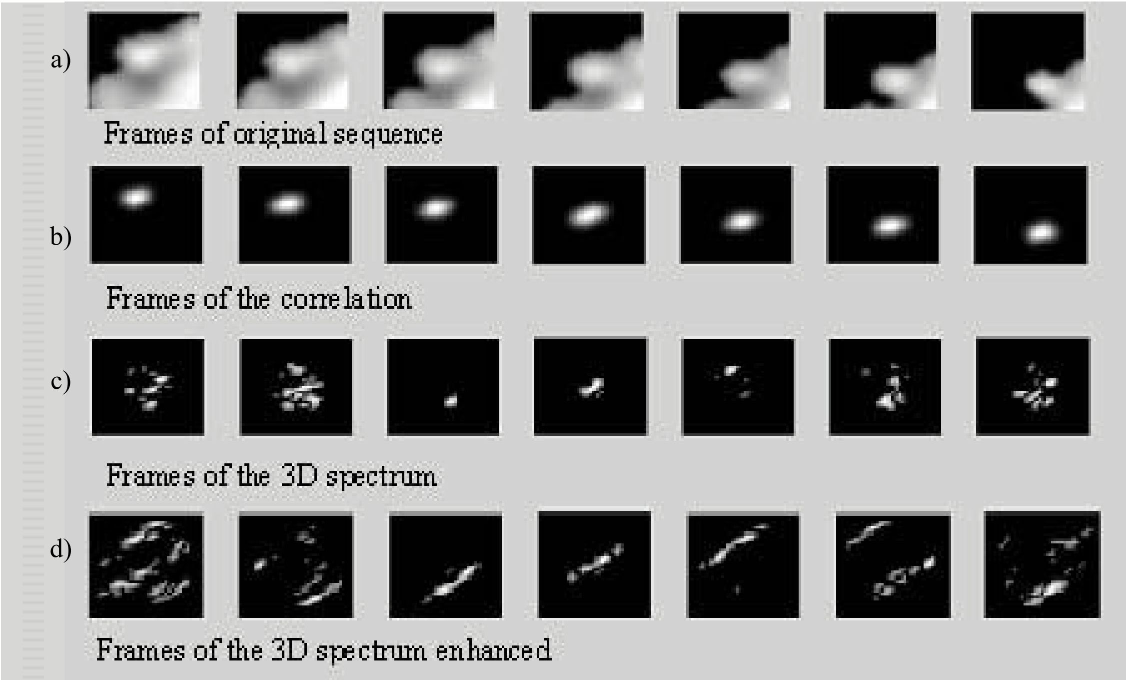


Fig. 8. a) Frames of a cropped region of a cardiac magnetic resonance. b) Correlation of the sequence. c) Spectrum obtained. d) Spectrum after processing the correlation.

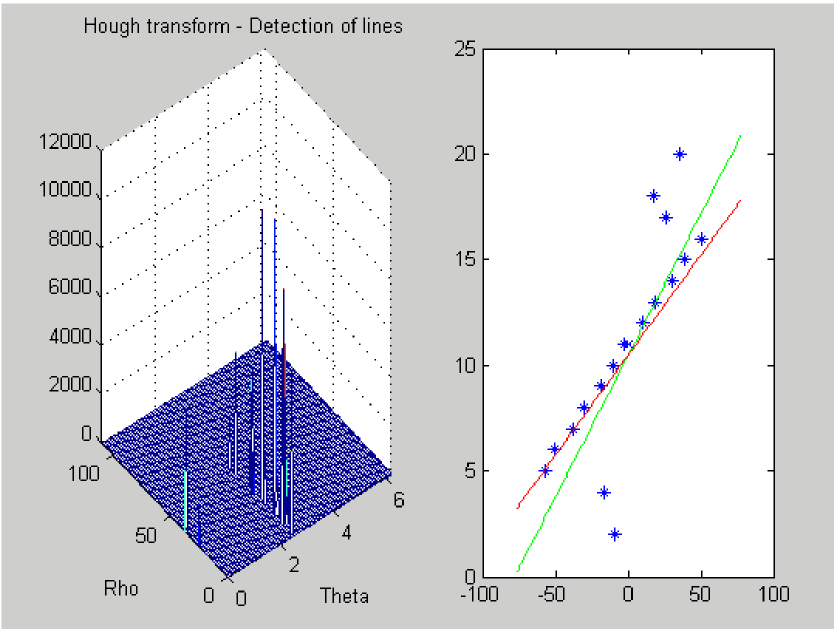


Fig. 9. a) Summation of all HT maxima. b) Values of ρ and estimation by LS (green line) and HT (red line).

Unfortunately, the ground truth is not provided in these real sequences, so it is not possible to achieve a quantitative result. In the example shown in Fig. 8 a velocity of v_x=0.38 pixels per frame and v_y=-0.5 pixels per frame has been obtained (where the window size was 20x20x20 pixels). Looking at the first and last image (Fig. 10), it is possible to make a qualitative evaluation of the result, which confirms its feasibility.

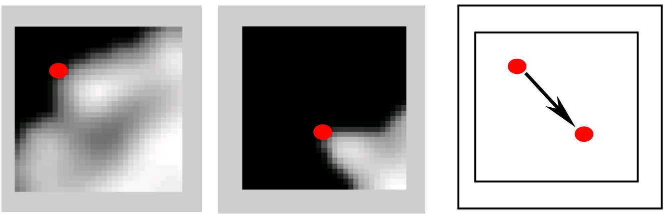


Fig. 10. a) First image of the selected region. b) Last image of the selected region. c) Qualitative movement.

The optical flow obtained for another sequence, taking frames of a systolic period is shown in Fig.11. Although the ground truth is not provided as it was mentioned before, a qualitatively assessment of the direction of the optical flow obtained confirms the movement of the myocardium.

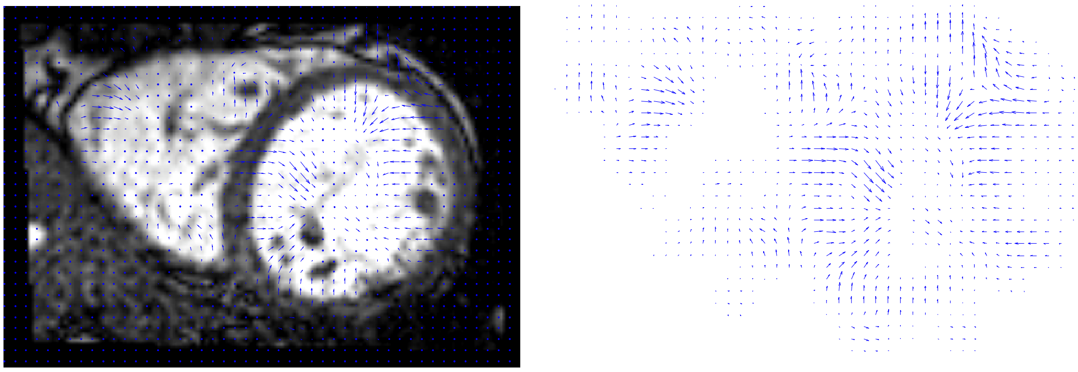


Fig. 11-a). Optical flow obtained during a period of systole superimposed on the first image of the sequence- b) Same optical flow obtained

5. CONCLUSIONS

In this paper, a frequency-based method for motion estimation based on the computation of the Wigner-Ville distribution together with the Hough Transform has been presented. Results from synthetic sequences have been shown, evaluated and compared with an implementation based on the variational method. The validated method has been applied also in real sequences of CMR.

The estimation of global motion gives values of optical flow very close to the actual ones. In this case, we can say that the solution is more accurate and robust to noise than the one obtained with the variational method. Nevertheless, a more fair comparison between both methods has been performed with a local estimation of motion. Selecting an appropriate size of window and using a hierarchical approach, the proposed method gives similar results to the variational approach.

The advantages brought by the WVD-HT method are the robustness to noise and the accuracy in global estimation of motion. In both methods, WVD-HT's and variational's, one of the major drawbacks is the selection of the optimum parameters for the algorithms.

The algorithm has been applied to real cardiac magnetic resonance sequences. Motion estimation in these sequences is very important for a fast a better diagnosis of cardiac diseases. Results obtained have been evaluated qualitatively. Further evaluation in clinical data should be addressed to confirm current promising results.

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REFERENCES

1. E. Simoncelli, "Distributed Representation and Analysis of Visual Motion", Thesis of Massachusetts Institute of Technology, 1993.
2. S.S. Beauchemin and J. L. Barron, "The Computation of Optical Flow", *ACM Computing Surveys*, vol. 27, No.3, pp. 433-467, September 1995.
3. W.I. Meyering, M.A. Gutierrez, S.S. Furuie, M.S. Rebelo, C.P. Melo, "Wigner-Ville Distribution applied to Cardiac Motion Estimation", Computers in Cardiology 2000, 2000, pp. 619-622.
4. B. K. P. Horn and B. G. Schunck, "Determining Optical Flow", Artificial Intell. 17, 1981, pp. 185-204.
5. G. Aubert, P. Kornprobst, Mathematical Problems in Image Processing: Partial Differential Equations and the Calculus of Variations, Springer-Verlag New York, LLC, 2001.
6. M. Pingault, D. Pellerin, "Motion estimation of transparent objects in the frequency domain", Signal Processing, vol. 84, pp. 709 – 719, April 2004.
7. L. Jacobson and H. Wechsler, "Derivation of optical flow using a spatiotemporal-frequency approach", Computer Vision, Graphics and Image Processing, vol. 38, pp. 29-65, 1987.
8. P. A. Laplante and A. D. Stoyenko, Real-time imaging: theory, techniques and applications, IEEE Press, 1996.
9. L. Jacobson and H. Wechsler, "Joint spatial/spatial-frequency representation", Signal Processing, vol. 14, pp. 37-68, 1998.
10. E. Wigner, "On the Quantum Correction for Thermodynamic Equilibrium", Physical Review, vol. 40, pp. 749-759, 1932.
11. E. Ville, "Théorie et Applications de la Notion de Signal Analytique", Cables et Transmission, 2A, pp. 61-74, 1948.
12. J. Hormigo and G. Cristóbal, "Image Segmentation Using the Wigner-Ville Distribution", Advances in imaging and electron physics, P.W. Hawkes (ed.), Academic Press, vol. 131, pp 65-80, 2003.
13. J. Bigun, "Vision with Direction: A systematic Introduction to Image Processing and Computer Vision", Springer-Verlag Berlin Heidelberg, 2006.
14. N. Aggarwal and W. C. Karl, "Line Detection in Images Through Regularized Hough Transform", IEEE Transactions on image processing, vol. 15, N. 3, pp. 582-591, March 2006.
15. J. S. Marques, "A probabilistic framework for the Hough Transform and Least Squares Pose Estimation", EUSIPCO 1998, Island of Rhodes, Greece, September 8-11. 1998.
16. R. O. Duda and P. E. Hart, "Use of the Hough Transformation to Detect Lines and Curves in Pictures", Communications of the ACM, vol. 15, No. 1, Jan. 1972.