A Deterministic Algorithm for Motion Estimation in Medical Image Sequences

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***Abstract* — This paper present a deterministic algorithm for motion estimation in medical image sequences. We are describing the Iterated Conditional Modes (ICM) adapted to solve the motion estimation problem in NMR image sequences. The proposed algorithm ensures a satisfying trade-off between precision and computational time or, in other words, ensure a good efficiency, comparing with the stochastic algorithms.**

The results are compared in term of precision and of computational time with some basic algorithms like the basic block-matching algorithm or the Horn & Schunck algorithm. The results are illustrated in the case of synthetic images (obtained using the Free Form Deformation principle) as well as real NMR medical image sequences.

I. INTRODUCTION

THE motion estimation in medical image sequences represents an open problem in medical imaging. This task is very important for the diagnosis of the moving organs in human body and especially to diagnosis the heart diseases. The most precise solution for motion estimation consist in using stochastic algorithms, in order to minimize an *a posteriori* energy, that include some *a priori* knowledge concerning the motion of the studied objects. These algorithms ensure the optimal solution but with a very high computational cost [7].

This is the reason why in practice we are using deterministic algorithms, in order to obtain a smaller computational time.

II. OVERVIEW ON MOTION ESTIMATION METHODS

The motion estimation methods could be classified as follows [13], [20]:

- differential methods;
- matching methods;
- stochastic methods.

The hypothesis that is made in all these methods is the preservation of the intensity of the pixels along the motion trajectory. This hypothesis could be expressed by the Displaced Frame Difference (DFD) equation [5], [10]:

$$DFD(\boldsymbol{p}) = I_t(\boldsymbol{p}) - I_{t-1}(\boldsymbol{p} - \boldsymbol{d}(\boldsymbol{p})) \quad (1)$$

where $\boldsymbol{p}=(x,y)$ is a pixel of the image, I_t and I_{t-1} are the images at t and t-1 instants and $\boldsymbol{d}(\boldsymbol{p})=(d_x(\boldsymbol{p}), d_y(\boldsymbol{p}))$ is the displacement of the pixel $\boldsymbol{p}$. This equation could be rewrite using the Taylor development [9]:

$$\frac{\partial I}{\partial x} v_x + \frac{\partial I}{\partial y} v_y + \frac{\partial I}{\partial t} = 0 \quad (2)$$

where v_x and v_y are the components of the velocity on x and y direction of the pixel $\boldsymbol{p}$. This equation is also known as Optical Flow Equation (OFE).

The performances of a motion estimation method [1], [2] depends on the properties of the images in the sequence, these properties depending themselves on the physical nature of the information that is represented in these images. The physical nature of the information depends on the acquisition method: ultrasounds (US), X rays or nuclear magnetic resonance (NMR).

The classical deterministic methods (differential and matching methods) are easy to be implemented but are not always sufficient precise [11], [19]. In addition, the motion estimation problem is an ill-posed problem: in order to obtain a unique and stable solution, we have to introduce some constraints [1]. The most precise solution for motion estimation consist in using stochastic algorithms, in order to minimize an *a posteriori* energy, that can include some *a priori* knowledge concerning the motion of the studied objects (for example the continuity of the displacement inside of the objects and the discontinuity at the objects frontiers) [3], [14]. These algorithms ensure the optimal solution but with a very high computational cost. The stochastic character of these methods is given by the minimization method that is used to minimize the *a posteriori* energy. Among these methods we can mention the simulated annealing. As an alternative of these stochastic minimization methods we can use deterministic methods [7], [16].

III. THE PROBABILISTIC APPROACH OF MOTION ESTIMATION

The probabilistic problem of motion estimation is the following: having the I_t and the I_{t-1} images, it has to determine the best estimation of the displacement field $\hat{\boldsymbol{d}}$ that maximize the probability: $p(\boldsymbol{d} \mid I_t, I_{t-1})$. This is the reason why this method is also known as Maximum A Posteriori (MAP) method. Using the Bayes formula and the Hammersley-Clifford theorem [7], [8], this formulation of the probabilistic motion estimation could be reformulated as finding the best estimation of the displacement field $\hat{\boldsymbol{d}}$ that minimize the energy:

$$\hat{\boldsymbol{d}} = \arg\min_{\boldsymbol{d}} \left[U\left(I_t \middle| \boldsymbol{d}, I_{t-1}\right) + \alpha \cdot U\left(\boldsymbol{d} \middle| I_{t-1}\right) \right] \quad (3)$$

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where α is a weighting coefficient between the two terms, $U(I_t|\boldsymbol{d},I_{t-1})$ is the term attached to the data (observed images) and $U(\boldsymbol{d}|I_{t-1})$ is the regularization term that express the *a priori* knowledge concerning the displacement field, as the continuity of the displacement inside of the objects and the discontinuity at the objects frontiers.

The regularization term could be view as a constraint that transforms the ill-posed motion estimation problem in a well-posed problem.

Supposing that the motion in the sequence is due only to the motion or to the noise, and supposing a white gaussian noise, with a zero mean and a σ standard deviation, we can use the following energy attached to the data [10]:

$$U(I_t|\,\boldsymbol{d},I_{t-1}) = \frac{1}{2\pi\sigma^2}\sum_{\boldsymbol{p}\in S} DFD^2(\boldsymbol{p}) \quad (4)$$

where S is the support of the image.

Another energy that could be used as energy attached to the data is [21]:

$$U(\nabla I\,|\,\boldsymbol{d}) = \frac{1}{2\pi\sigma^2}\sum_{\boldsymbol{p}\in S}\cdot\left[d_x(\boldsymbol{p})\cdot\frac{\partial I(\boldsymbol{p})}{\partial x} + d_y(\boldsymbol{p})\cdot\frac{\partial I(\boldsymbol{p})}{\partial y} + \frac{\partial I(\boldsymbol{p})}{\partial t}\right]^2 \quad (5)$$

where: $\nabla I = \left(\frac{\partial I}{\partial x},\frac{\partial I}{\partial y},\frac{\partial I}{\partial t}\right)$ is supposed known.

As a regularization term of the displacement field in (3) we can use the following energy:

$$U(\boldsymbol{d}|I_{t-1}) = \sum_{c\in C_d} V_d^c(\boldsymbol{d}|I_{t-1}) \quad (6)$$

where c is a pair (clique) of pixels in the neighborhood (on the displacement field) of the current pixel, C_d represents the ensemble of all the pairs that could be defined on the neighborhood of the current pixel and $V_d^c(.)$ is the potential of the pair c defined on the displacement field $\boldsymbol{d}$. An example of a potential of a clique of the second order (pair of 2 pixels) is [3]:

$$V_d^{c_2}(\boldsymbol{d}(\boldsymbol{p}),\boldsymbol{d}(\boldsymbol{r})) = \|\boldsymbol{d}(\boldsymbol{p}) - \boldsymbol{d}(\boldsymbol{r})\|^2 \quad (7)$$

where $\boldsymbol{p}$ and $\boldsymbol{r}$ are the pixels of the clique c_2 and $\|.\|$ is the Euclidian norm. For this example, a spatial configuration of the motion field with a high potential will have a low *a priori* probability.

Thus, in the probabilistic motion estimation we have to minimize the MAP energy described in (3):

$$\boldsymbol{U_{MAP}} = U(I_t|\,\boldsymbol{d},I_{t-1}) + \alpha\cdot U(\boldsymbol{d}|I_{t-1}) \quad (8)$$

IV. THE ICM ALGORITHM FOR MOTION ESTIMATION

The minimization of the MAP energy is complex because this energy is usually non-convex and thus, it admits local minima.

The minimization algorithms could be classified in:

- stochastic algorithms;
- deterministic algorithms.

Among the stochastic algorithms a very used algorithm is the simulated annealing (Monte-Carlo type) algorithm [7] and the genetic algorithm. These algorithms ensure the optimal solution of the MAP energy but with a very high computational cost [[15]].

The deterministic algorithms are fasters but they present the disadvantage that they could remain "hanged" in a local minima. Among the deterministic algorithms the most used algorithms are [20], [22]:

- iterated conditional modes (ICM);
- gradual non-convexity (GNC);
- mean field annealing (MFA).

We will describe the ICM algorithm that is a very used algorithm in many image processing applications. In the following, we will present an application of this algorithm in the case of motion estimation.

The general principle of the ICM algorithm could be resumed as in the diagram (9).

1. *Initialization* $I_{(0)}$ *;*
2. *Calculate* $I_{(k+1)}$ *starting from* $I_{(k)}$ *:*
   - *(a) scanning all the pixels* **p** *(according to a scan strategy):*

     $$I_{(k+1)}(\boldsymbol{p}) = \arg\min_{\boldsymbol{d}} U_{MAP}\left(I_{(k)}(\boldsymbol{p})\,|\,I_{(k)}(\boldsymbol{r})\right),\quad \boldsymbol{r}\in N_{\boldsymbol{p}} \quad (9)$$

     $k=k+1$*;*
   - *(b) Jump in (a) until a stopping criteria.*

In the case of the ICM algorithm for motion estimation, starting from an initialization $I_{(0)}$ of the motion field we are scanning cyclically all the pixels $\boldsymbol{p}$ of the image I, according to a scanning strategy. each iteration, we are modifying only the displacement corresponding to one pixel and it is minimized the energy:

$$U_{MAP}\left(I_{(k)}(\boldsymbol{p})\,|\,I_{(k)}(\boldsymbol{r})\right) \quad (10)$$

that corresponds to the probability of the realization of a certain value of the displacement corresponding to the pixel $\boldsymbol{p}$, conditioned by the realization of a certain configuration of the displacements of the pixels $\boldsymbol{r}$ in a neighborhood of the pixel $\boldsymbol{p}$. In the iterative process the value of the displacement of each pixel is scanning the entire range of the possible values. It can be shown that at each iteration the corresponding energy (10) decrease. Thus, weighting a good initialization we can obtain a good estimation.

The ICM algorithm converges quicker than stochastic algorithms, but it converge to a local minima because it doesn't accept negative variations of the MAP energy. A problem of the ICM algorithm is to choose a good estimation.

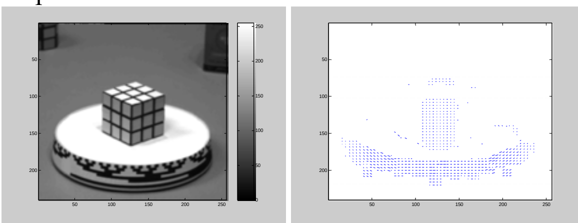
If the number of possible values is small, as it is the maximum displacement in the case of motion estimation, the ICM algorithm converges very quickly (1…5 iterations) [16].

Comparing with differential methods and matching methods, the probabilistic motion estimation methods allow us to take into account the discontinuities of the motion field, in order to increase the precision of the estimation.

V. RESULTS

We will present some comparative results, in terms of precision and computational time, between the Horn & Schunck (HS) method, the exhaustive block-matching (BM) method and the MAP method, using the ICM as a minimization algorithm.

In figure 1, the results in the case of a reference sequence in motion estimation (Rubic Cube sequence) are presented.



(a) (b)

Figure 1. Results in the case of Rubic Cube sequence.

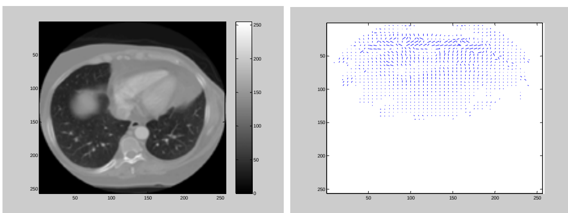
In figure 1 (a) the first image of the Rubic Cube sequence is presented. In figure 1 (b) the estimated motion field is illustrated. The motion field was estimated using the MAP method, with ICM.

In table 1, the comparative numerical results are presented, for HS, BM and MAP method.

TABLE 1. COMPARATIVE RESULTS FOR RUBIC CUBE SEQUENCE.

Estimation method	Mean Value	Standard Deviation
HS	-0.74	3.32
BM	-1.02	11.86
MAP	0.01	2.39

In figure 2 the results in the case of a synthetic sequence (FFD) is presented. This sequence was obtained using the Free Form Deformation (FFD) principle [17] and is simulating a breath movement of a thorax.



(a) (b)

Figure 2. Results in the case of FFD sequence.

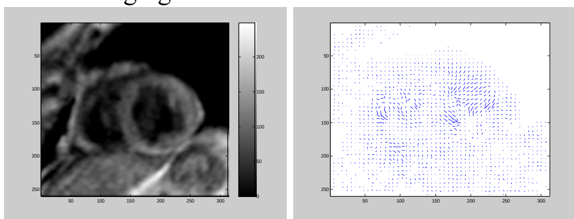
In figure 2 (a) the first image of the synthetic sequence (FFD) is presented. In figure 2 (b) the estimated motion field is illustrated. The motion field was estimated using the MAP method, with ICM.

In table 2, the comparative numerical results are presented, for HS, BM and MAP method.

TABLE 2. COMPARATIVE RESULTS FOR FFD SEQUENCE.

Estimation method	Mean Value	Standard Deviation
HS	0.19	1.33
BM	1.06	4.97
MAP	0.11	1.20

In figure 3, the results in the case of a real sequence (IRM) are presented. This sequence is obtained using a NMR imaging method of a human heart.



(a) (b)

Figure 3. Results in the case of IRM sequence.

In figure 3 (a) the first image of the real sequence (IRM) is presented. In figure 3 (b) the estimated motion field is illustrated. The motion field was estimated using the MAP method, with ICM.

In table 3, the comparative numerical results are presented, for HS, BM and MAP method.

TABLE 3. COMPARATIVE RESULTS FOR IRM SEQUENCE.

Estimation method	Mean Value	Standard Deviation
HS	-0.14	1.17
BM	0.122	4.17
MAP	-0.11	1.05

As we can observe from the presented results, the most precise results are obtained for the MAP estimation method. In this method we have used as energy attached to the data, the energy that was described in equation (5) and as energy of displacement regularization we have used the energy described in (6) and (7). But using this method, with the described energies, we will impose a uniform regularization of the displacement field in the entire image, without taking into account the discontinuities in the displacement field, that usually corresponds to the gray-level discontinuities.

In terms of computational time, the MAP method with ICM gives us a still high computational time, as it can be observed in table 4 [8].

TABLE 4. COMPARATIVE COMPUTATIONAL TIME.

	HS	BM	ICM
Computational time [s]	0.7	1.36	27.52

Even the MAP+ICM computational time is smaller that a stochastic algorithm (minutes or hours), it is still high comparing with classical algorithms (HS and BM). In addition, the use of the energy attached to the data (5) not allows us to estimate great displacement, because of the well known problem of the differential methods: the approximation of the partial derivates as finite differences, in a small neighborhood. In order to decrease the computational time and to can estimate bigger displacements, we can use a multi-resolution approach [15]. In order to increase the precision, we can use a MAP method but introducing some *a priori* knowledge, for example introducing the discontinuities of the displacement field [14]. In order to decrease the computational time, we can implement this method or some parts of it on dedicated hardware structure as, for example, the Cellular Neural Networks (CNN) [4].

VI. CONCLUSIONS

We have presented the MAP method adapted for motion estimation method, using as minimization method the ICM algorithm that allows us to introduce some *a priori* knowledge. The results is satisfying in terms of precision, but in terms of computational time, even if it give us a smaller computational time then the stochastic algorithms, it still have a great computational time, comparing with classical motion estimation methods (HS and BM).

It remains as a future work, to implement the multi-resolution version of the MAP+ICM algorithm, in order to decrease the computational time and to can estimate bigger displacements. In order to increase the precision, we will develop the MAP method introducing some *a priori* knowledge, namely the discontinuities of the displacement field. We will also try to implement this method or some parts of it on a dedicated parallel hardware as the Cellular Neural Networks (CNN) [12], [18], in order to decrease the computational time.

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