Motion Estimation in the Frequency Domain Using Fuzzy C-Planes Clustering

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***Abstract*—A recent work explicitly models the discontinuous motion estimation problem in the frequency domain where the motion parameters are estimated using a harmonic retrieval approach [1], [2]. The vertical and horizontal components of the motion are independently estimated from the locations of the peaks of respective periodogram analyses and they are paired to obtain the motion vectors using a procedure proposed in [1]. In this paper, we present a more efficient method that replaces the motion component pairing task and hence eliminates the problems of the pairing method described in [1]. The method described in this paper uses the fuzzy c-planes (FCP) clustering approach [3]–[5] to fit planes to three-dimensional (3-D) frequency domain data obtained from the peaks of the periodograms. Experimental results are provided to demonstrate the effectiveness of the proposed method.**

***Index Terms*—Frequency estimation, fuzzy c-planes (FCP), fuzzy clustering, motion estimation.**

I. Introduction

Motion estimation is an important problem in video processing that is utilized in many applications such as video coding, object-based video manipulation, object-based segmentation, and dynamic scene analysis. Many studies have been carried out in an effort to estimate the motion of the objects in a scene [2], [6]–[10]. There are a number of approaches based on the correlation methods [6], [8], and the optical flow constraint [6]–[8]. These methods generally use regularization techniques assuming the smoothness of the motion field in order to obtain a unique solution. This smoothness assumption has an unwanted side effect of over-smoothing the motion discontinuities.

In a recent work [1], [2], the discontinuous motion estimation problem is handled in a harmonic retrieval framework. In this approach, the motion discontinuities are explicitly modeled and the velocity estimation is carried out independently of the shape of the moving object and the density of motion discontinuities. The moving objects are assumed to have different translational motion parameters and the motion is assumed to be time-invariant in a short time interval. In order to find the motion parameters, first, horizontal and vertical component sets along with their corresponding sums are estimated from the peak locations of periodogram analyses [1]. Periodogram analysis is a nonparametric method for spectrum estimation. A component pairing approach follows this step which is prone to errors. In this work, we present a more robust method for estimation of the motion parameters, which uses the three-dimensional (3-D) frequency domain data and fits planes to them via the fuzzy c-planes (FCP) clustering method [3]–[5]. This approach has been indicated in [1] as future work with no results given.

In Section II, the theoretical background for modeling the motion estimation problem in the frequency domain [1] is introduced. In Section III, the motion parameter estimation method using the FCP clustering approach is presented. In Section IV, the experimental results are given and compared with the pairing method of [1]. In Section V, concluding remarks are given.

II. Theoretical Background

In this section, the multiple discontinuous motion modeling approach described in [1] is briefly summarized. The reader should refer to [1] for a detailed explanation of notation and equations.

Given an image sequence, it is assumed that there exists N (including the background) objects (partitions) in the scene at time t, i.e.

$$W(t) = \bigcup_{l=1}^{N} W_l(t), \qquad W_l(t) \cap W_n(t) = \emptyset, \quad \forall l \neq n \tag{1}$$

where $W(t)$ denotes the region of interest of the image at time t and $W_l(t)$ is the support region of object l. Let $f_{Il}(x,y)$ denote the "ideal" image of object l, at time $t=0$, if there were no occlusion. Let the parameters $(u_i, v_i),\ i = 1, \ldots, N$, denote the motion vectors of the objects, which are assumed to be constant in a short time interval T. Then, the image sequence $f(x,y;t),\ t = 0, \ldots, T$, can be represented as [1]

$$f(x,y;t) = \sum_{l=1}^{N} f_{Il}(x - u_l t, y - v_l t)\, w_l(x,y;t) \tag{2}$$

where $w_l(x,y;t)$ denotes the indicator function representing $W_l(t)$, which takes the value 1 if $(x,y) \in W_l(t)$ and takes the value 0 otherwise.

Manuscript received December 8; 2000; revised October 4, 2001. This work was supported by the Scientific and Technical Research Council of Turkey (TÜBİTAK-BAYG) and Boğaziçi University Research Fund under Project 99A207. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Christoph Stiller.

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Publisher Item Identifier S 1057-7149(01)10557-9.

After some manipulations [1], (2) can be written as

$$f(x,y;t) = \sum_{l=1}^{N} f_{vl}(x-u_l t, y-v_l t) + e(x,y;t) \quad (3)$$

$$f_{vl}(x-u_l t, y-v_l t) = f_{Il}(x-u_l t, y-v_l t) \times \bar{w}_{l0}(x-u_l t, y-v_l t) \quad (4)$$

where f_{Il} is the ideal image of object l and $\bar{w}_{l0}$ denotes its corresponding average support window over T frames [1]

$$\bar{w}_{l0}(x,y) = \frac{1}{T}\sum_{t=0}^{T} w_l(x+u_l t, y+v_l t; t). \quad (5)$$

The term

$$e(x,y;t) = \sum_{l=1}^{N} f_{Il}(x-u_l t, y-v_l t)\, d_l(x,y;t) \quad (6)$$

denotes the error, where d_l denotes the difference between the support window of object l at time t and its shifted average support window. The two-dimensional (2-D) spatial Fourier transform of (3) gives

$$F(w_x,w_y;t) = \sum_{l=1}^{N} F_{vl}(w_x,w_y)\, e^{-j(w_x u_l + w_y v_l)t} + E(w_x,w_y;t). \quad (7)$$

When the (w_x, w_y) pair is fixed, $F(w_x, w_y; t)$ is a one-dimensional (1-D) signal consisting of N harmonics in noise where the frequency of the lth harmonic is

$$w_l = -w_x u_l - w_y v_l, l = 1, \ldots, N. \quad (8)$$

Our aim is to estimate the motion parameters (u_l, v_l), $l = 1, \ldots, N$. Periodogram analysis is a classical method for estimating the parameters of harmonics in noise [11] and is based on the Fourier transform of the data sequence. Another method for frequency estimation is the MUltiple SIgnal Classification (MUSIC) algorithm [12], which can provide a higher resolution than the periodogram. For a specific (w_x, w_y) pair, the periodogram of $F(w_x, w_y; t)$ which is based on its temporal Fourier transform is given by

$$I_F(w_x,w_y;w) = \frac{1}{T}\left|\sum_{t=0}^{T-1} F(w_x,w_y;t)\, e^{-jwt}\right|^2 \quad (9)$$

the peaks of which give the component frequencies $w = -w_x u_l - w_y v_l$, as a function of the motion parameters. In [1], the peaks of the periodograms of $F(w_x, 0; t)$, $F(0, w_y; t)$, and $F(w_x, w_x; t)$ are determined to estimate the motion parameter sets in the x and y directions and the set consisting of the sum of these two velocity components, respectively. Then the motion parameter sets in the x and y directions are paired such that

$$\sum_{i=1}^{N} (a_i + b_i - c_i)^2 \quad (10)$$

is minimized where a_i, b_i, and c_i are members of the sets consisting of the motion parameters in the x and y directions and their sums, respectively [1]. The parameter N indicates the number of objects in the scene with distinct motion parameters and is estimated as the maximum of the number of elements of the three velocity sets described above.

This approach may give erroneous results in some cases. For example, if we have three objects in our scene moving with motion parameters $(u_1, v_1) = (0, -2)$, $(u_2, v_2) = (-2, 0)$, and $(u_3, v_3) = (-2, -2)$, the above pairing method of [1] will find the number of moving objects in the scene as $N = 2$, since all the velocity sets will contain two elements. To be more specific, the set consisting of the x-components of the velocities will be $\{0, -2\}$, the set consisting of the y-components of the velocities will be $\{-2, 0\}$, and the set consisting of the sum $u_l + v_l$ will be $\{-2, -4\}$. In the next section, we propose another method based on fuzzy c-means clustering that eliminates the need for pairing the velocity components using (10).

III. Motion Parameter Estimation Using Fuzzy C-Planes Clustering

In this section, we present another approach for simultaneous motion parameter estimation and pairing which is based on the FCP clustering algorithm [3]–[5]. This approach overcomes the difficulties of the pairing method of [1].

For different (w_{x_i}, w_{y_i}) pairs, the peaks of the periodogram of (9) are estimated and the 3-D data are formed as

$$h_i = (w_{x_i}, w_{y_i}, w_i) \quad (11)$$

where w_i denotes the location of a peak. There may be more than one dominant peak for a specific (w_{x_i}, w_{y_i}) pair.

Note that, since these 3-D points satisfy the equation

$$w_i = -w_{x_i} u_l - w_{y_i} v_l, l \in \{1, \ldots, N\} \quad (12)$$

they are expected to form N planes in 3-D frequency domain. The plane parameters are the negatives of the motion parameters. We estimate the plane parameters via clustering these 3-D data into N planes. The estimated plane parameters give us the motion parameters without the need for a pairing step.

In order to cluster the above 3-D frequency domain points into N planes, we use the FCP algorithm [3]–[5]. The FCP algorithm uses all of the sampled 3-D data vectors as given in (11), for different values of (w_x, w_y), instead of some specific values of (w_x, w_y). The FCP is a probabilistic clustering method which minimizes the following cost function:

$$J_{\mathrm{FCP}} = \sum_{i=1}^{M}\sum_{j=1}^{N} u_{ij}^q d_{ij}^2 \quad (13)$$

where M is the total number of 3-D data points, N is the number of planes, u_{ij} is the membership value of the ith data vector to the jth plane, d_{ij} is the distance between the ith data vector, and the jth plane and q is the fuzzifier which is a weight parameter. The FCP method is “fuzzy” in the sense that at each iteration, a data vector belongs to each of the classes to a certain degree. The above cost function denotes the weighted average of the distance between the data points and their assigned planes. The distance is calculated as given in (18), where v_j is a point which characterizes normalized centroid of the jth plane. The membership parameter is subject to the constraints given in (14) and (15). In order to minimize the cost function (13), the derivatives of J_{FCP} with respect to d_{ij} and v_j are calculated, which give us the expressions (16) and (19) (for details, see [5]). The steps of the alternating optimization algorithm that minimizes the cost function (13) are given below.

Step 1) Initialize each membership value u_{ij}, randomly such that the constraints

$$0 \le u_{ij} \le 1, \quad i = 1, \ldots, M, \quad j = 1, \ldots, N \tag{14}$$

and

$$\sum_{j=1}^{N} u_{ij} = 1, \quad \forall i \tag{15}$$

are satisfied. Inspecting the 3-D plot of the data vectors (h_i's) visually to set simple thresholds may also be helpful in initializing the algorithm close to the desired local minimum when the data is noisy.

Step 2) Estimate each normalized cluster centroid, v_j using the equation

$$v_j = \frac{\sum_{i=1}^{M} u_{ij}^q h_i}{\sum_{i=1}^{M} u_{ij}^q}, \quad j = 1, \ldots, N. \tag{16}$$

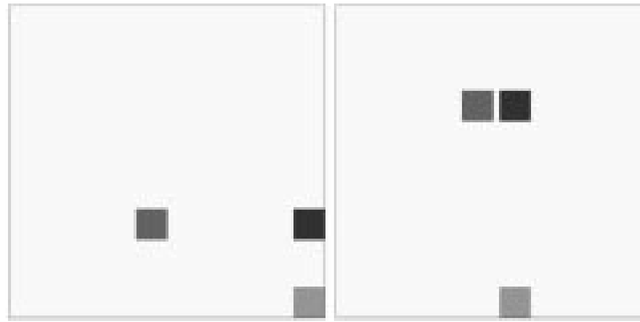
Here, h_i denotes the data vectors as defined in (11) and q is a parameter that represents the amount of fuzziness of the clustering. The larger the q is, the fuzzier the clustering becomes, since the weighting factor u_{ij}^q will become closer to zero faster. For example, if $u = 0.9$ and $q = 10$, then the weight u^q will be 0.3487. If q is chosen to be large, this may cause the (local) minima of the cost function to be less clearly distinguishable. However, choosing a large value for q may help to reduce the effect of noisy data by minimizing its weight [3]. A frequently chosen value for q is 2 [5].

Step 3) Estimate the covariance matrix of each cluster (plane), R_j, as follows:

$$R_j = \frac{\sum_{i=1}^{M} u_{ij}^q (h_i - v_j)(h_i - v_j)^T}{\sum_{i=1}^{M} u_{ij}^q}, \quad j = 1, \ldots, N. \tag{17}$$

Step 4) Find the distance of each data point to each of the current clusters (planes). These distances will be used in the next step to update the membership values. Since the data points of each cluster are expected to lie on a plane, which is spanned by two vectors, the largest two eigenvectors of R_j (V_{j1} and V_{j2}) are found and the squared distance between the data point i and the plane j is estimated as follows:

$$d_{ij}^2 = \|h_i - v_j\|^2 - \sum_{k=1}^{2} \left((h_i - v_j)^T V_{jk} \right)^2, \forall i, j. \tag{18}$$



(a) (b)

Fig. 1. (a) First and (b) 20th frames of the sequence containing three moving blocks.

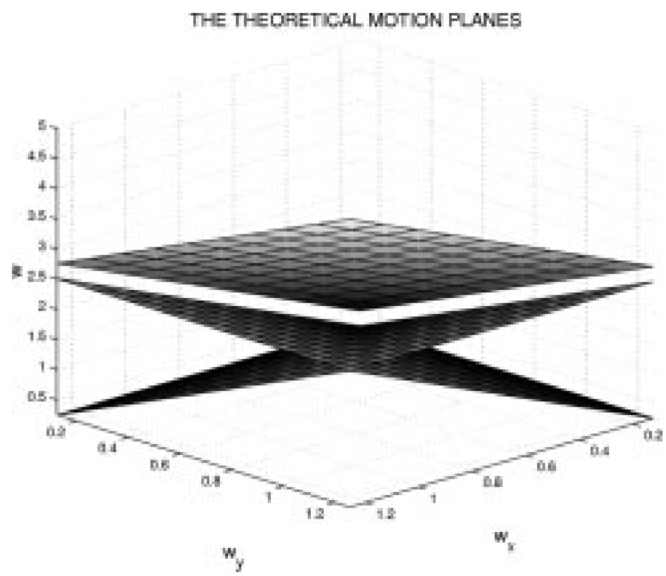


Fig. 2. Theoretical motion planes for the sequence containing three moving blocks.

The above equation calculates the perpendicular distance from the data point h_i to the estimated plane j. The first term is the squared of the distance between the data point h_i and the cluster centroid v_j. The second term finds the projection of the vector from v_j to h_i onto each of the eigenvectors of the plane and subtracts them from the first term to find the perpendicular distance.

Step 5) Update the membership values of the data points as follows:

$$u_{ij} = \frac{\left(d_{ij}^2\right)^{-1/(q-1)}}{\sum_{k=1}^{N} \left(d_{ik}^2\right)^{-1/(q-1)}}, \quad i = 1, \ldots, M; \quad j = 1, \ldots, N. \tag{19}$$

Step 6) Repeat the steps 2–5 until the change in the membership values between two successive iterations is below a certain error threshold ε, i.e.,

$$\|u_{ij}^s - u_{ij}^{s+1}\| < \varepsilon \tag{20}$$

where s denotes the iteration number.

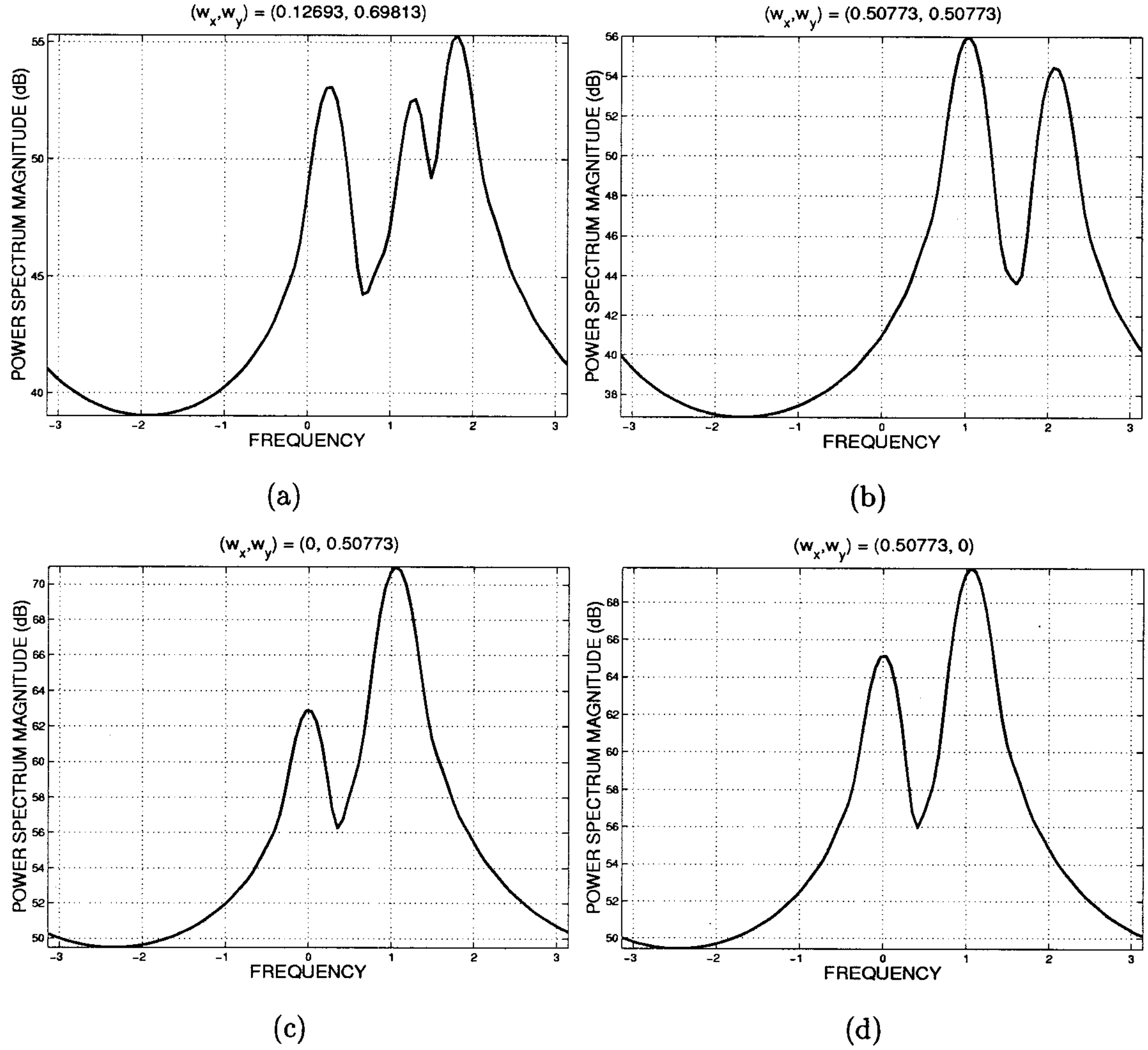


Fig. 3. Periodogram plots for different (w_x, w_y) pairs: (a) $(w_x, w_y) = (0.127, 0.698)$; (b) $(w_x, w_y) = (0.508, 0.508)$; (c) $(w_x, w_y) = (0, 0.508)$; and (d) $(w_x, w_y) = (0.508, 0)$.

Step 7) Estimate motion parameters of each object using the eigenvectors of each plane.

When the number of planes is not known a priori, the numerical value of the cost function $J_{\rm FCP}$ can be used to estimate it. The cost function $J_{\rm FCP}$ decreases for increasing values of N. However, the decrease occurs in larger steps until the correct number of planes is reached and the cost function decreases in smaller steps afterwards. This property is used to estimate the number of planes as described in the next section.

IV. Experimental Results

The proposed method is first tested using a synthetically generated sequence, which contains three moving blocks on a stationary background. Two frames of this sequence are shown in Fig. 1. The motion vectors for the three blocks are $(u_1, v_1) = (-2, -2)$, $(u_2, v_2) = (-2, 0)$, and $(u_3, v_3) = (0, -2)$ in the northwest direction. The theoretical motion planes in the 3-D frequency domain are shown in Fig. 2. The top plane corresponds to the motion vector $(u_1, v_1) = (-2, -2)$ and the other planes correspond to the motion vectors $(u_2, v_2) = (-2, 0)$ and $(u_3, v_3) = (0, -2)$. In Fig. 3, several periodogram plots are given for different (w_x, w_y) pairs. Note that three peaks are clearly visible in Fig. 3(a), whereas only two peaks exist when $w_x = w_y$, as shown in Fig. 3(b) and when w_x or w_y is close to zero as shown in Fig. 3(c) and (d). The peaks of the periodogram are estimated using the *pickpeak* function of MATLAB which simply uses the derivatives of the periodogram. Some spurious peaks are eliminated afterwards if the magnitude of the peak is smaller than a certain fraction (0.3) of the maximum peak. The 3-D data extracted from the peak locations of the periodograms are shown in Fig. 4. In order to estimate the number of objects, we plotted the cost function (13) for different number of planes as shown in Fig. 6. The cost function decreases sharply until $N = 3$ and the remaining part of the plot is almost flat. This shows that the number of objects in the scene is three. The estimated velocities are close to the true values, as tabulated in Table I, and as demonstrated in Fig. 5. Using FCP clustering, the velocities of the three moving objects are correctly estimated, whereas this is not possible with the pairing approach of [1], as discussed in Section II.

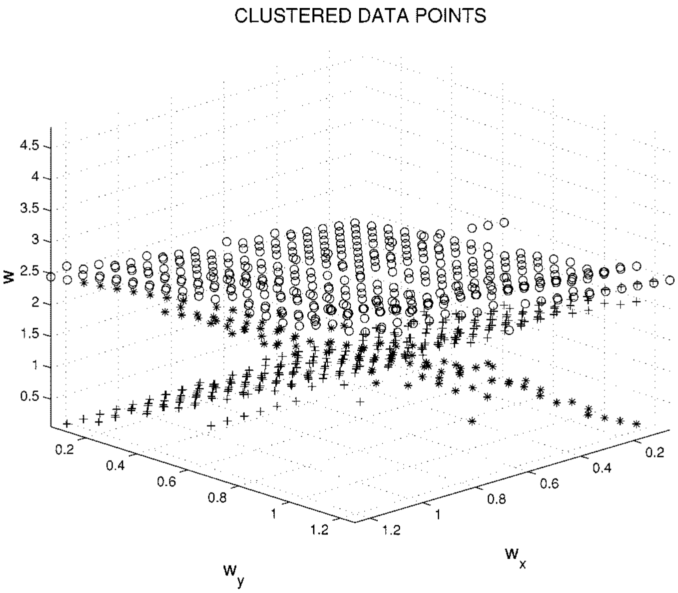


Fig. 4. Data points obtained from the peak points of the periodogram for the synthetic sequence. The symbols 'o,' '$*$,' and '$+$' represent data points belonging to different planes estimated by the FCP clustering algorithm.

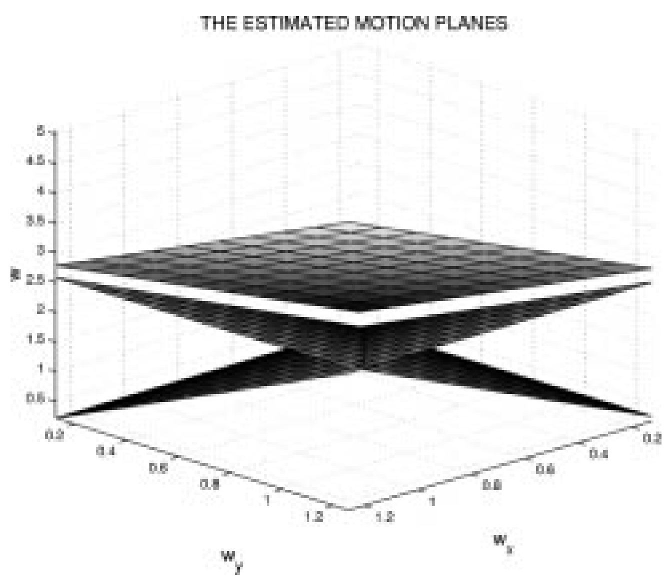


Fig. 5. Motion planes estimated using the clustered data shown in Fig. 4.

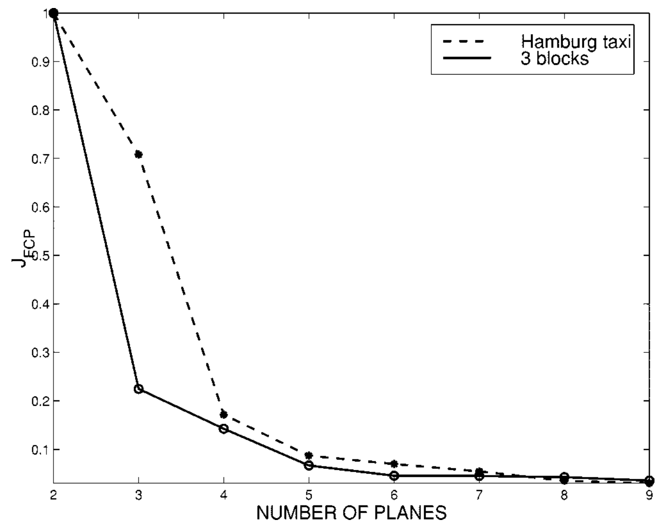


Fig. 6. Cost function versus number of planes. The solid line marked with 'o' signs is for the sequence with three moving blocks and the dashed line marked with '$*$' signs is for the "Hamburg Taxi" sequence. The magnitudes have been scaled so that the maximum cost value is mapped to one.

TABLE I
THE ORIGINAL AND ESTIMATED MOTION VECTORS FOR THE SEQUENCE CONTAINING THREE MOVING BLOCKS

ORIGINAL VECTORS	ESTIMATED VECTORS
$(u_1, v_1) = (-2, -2)$	$(\hat{u}_1, \hat{v}_1) = (-2.018, -2.018)$
$(u_2, v_2) = (-2, 0)$	$(\hat{u}_2, \hat{v}_2) = (-2.060, -0.071)$
$(u_3, v_3) = (0, -2)$	$(\hat{u}_3, \hat{v}_3) = (0.009, -2.044)$

(a) (b)

Fig. 7. The (a) 1st and (b) 20th frames of the "Taxi in Garden" sequence.

Another sequence that we used for testing the plane-fitting approach is the "Taxi in Garden" sequence, which is shown in Fig. 7. In this sequence, the white taxi moves with a velocity vector of $(3, -1)$ in the northeast direction. As a preprocessing step, we applied histogram equalization in order to enhance the contrast. Although the background is cluttered, the plane fitting approach was able to estimate the velocity vector as $(2.9948, -0.98736)$.

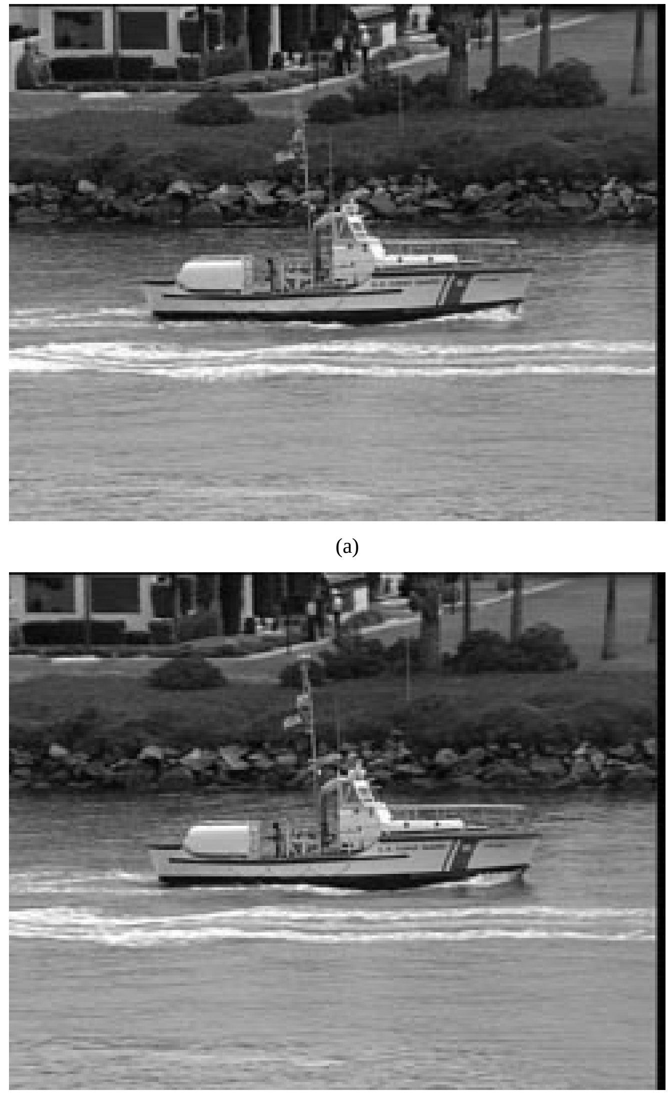
We also used two natural sequences to test the algorithm. The first one is the "Hamburg Taxi" sequence which is shown in Fig. 8. The spectrum analyses are done using the MUSIC algorithm [12]. The true velocity values are determined by manual feature point tracking [1]. As seen in Table II, the estimated motion parameters are quite close to the actual values. The first three rows of Table II give the motion parameters of the three vehicles and the last row gives the parameters of the stationary background. The walking person in the upper left corner is not detected since it is too small. The cost function (13) for different number of planes is shown in Fig. 6. The cost function decreases sharply until N increases up to four, and the rest of the plot is almost flat indicating that the number of objects in the scene is four.

The second natural sequence used for testing the algorithm is the "Coast Guard" sequence, which is shown in Fig. 9. Between the 130th and the 140th frames, the boat moves toward right and the background translates toward left due to the motion of the camera. The true values of the motion vectors are estimated by manual feature point tracking. Table III shows the true and estimated values of the motion vectors. The first row of Table III

(a)

(b)

Fig. 8. The (a) 1st and (b) 20th frames of the "Hamburg Taxi" sequence.



(a)

(b)

Fig. 9. The (a) 130th and (b) 140th frames of the "Coast Guard" sequence.

TABLE II
THE ORIGINAL AND ESTIMATED MOTION VECTORS FOR THE "HAMBURG TAXI" SEQUENCE

ORIGINAL VECTORS	ESTIMATED VECTORS
$(u_1, v_1) = (2.7, 0.45)$	$(\hat{u}_1, \hat{v}_1) = (2.971, 0.618)$
$(u_2, v_2) = (-2.65, -0.35)$	$(\hat{u}_2, \hat{v}_2) = (-2.243, -0.334)$
$(u_3, v_3) = (-0.83, -0.45)$	$(\hat{u}_3, \hat{v}_3) = (-1.0782, -0.723)$
$(u_4, v_4) = (0, 0)$	$(\hat{u}_4, \hat{v}_4) = (0.0015, -0.005,)$

TABLE III
THE ORIGINAL AND ESTIMATED MOTION VECTORS FOR THE "COAST GUARD" SEQUENCE

ORIGINAL VECTORS	ESTIMATED VECTORS
$(u_1, v_1) = (0.36, -0.18)$	$(\hat{u}_1, \hat{v}_1) = (0.3014, -0.1334)$
$(u_2, v_2) = (-1.52, -0.2)$	$(\hat{u}_2, \hat{v}_2) = (-1.7005, -0.3907)$

gives the motion parameters of the boat and the second row gives the parameters of the background. Note that although the motion in the scene is not purely translational due to the waves in front of the boat, the flag, and the person on the boat, the estimated motion vectors are reasonably close to the true values.

V. CONCLUSIONS

In this paper, we presented an alternative approach for the pairing and motion parameter estimation problem of [1]. The presented method is based on fitting planes to the 3-D data in the frequency domain using FCP algorithm. The parameters of these planes correspond to the horizontal and vertical motion parameters of the objects in the scene. This approach eliminates the need to pair the velocity components of the objects [1]. The experiments on synthetic and natural image sequences demonstrate the effectiveness of the proposed method.

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