Object Tracking Algorithm for Multimedia System

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ABSTRACT

In this paper, we propose a new scheme of motion tracking based on fuzzy inference (FI)and wavelet transform (WT) from image sequences. First, we present a WT to segment a feature extraction of dynamic image . The coefficient matrix for 2-level DWT tent to be clustered around the location of important features in the images, such as edge discontinuities, peaks, and corners. But these features are time varying owing to the environment conditions. Second, to reduce the spatio-temporal error, We develop a fuzzy inference algorithm. Some experiments are performed to testify the validity and applicability of the proposed system. As a result, proposed method is relatively simple compared with the traditional space domain method. It is also well suited for motion tracking under the conditions of variation of illumination.

I. INTRODUCTION

Pattern recognition concepts have become increasingly recognized as an important factor in such varied fields as character recognition, fingerprint, machine vision and considerable outputs have been reported. Lots of pattern recognition methods have fully discussed in several references [1][2], and generally, this procedure can be divided into two basic steps. one is a process of extraction/detection of the features so-called preprocessing. the other is a classification/ identification process which is based on knowledge -knowledge about objects and their classes gives the necessary information for object classification [3][4].

In order to recognize the more detail and efficient both specific knowledge about the processed objects and hierarchically higher and more general knowledge about classes are often required.

In this approach, we address the object recognition scheme by using DWT and FI.

After segmentation, Some feature parameters calculated from the coefficients matrix of DWT. in the motion tracking stage, two procedures are involved: inference rule generation process and composition operation process.

A method for extracting feature parameters based on DWT is described in section Ⅱ. In section Ⅲ, we present some background of fuzzy inference including recognition algorithm. Experiments are reported in section Ⅳ including the test model.

II. DWT BASED SEGMENTATION OF FEATURE PARAMETERS

A major objective of transform coding is to make as many transform coefficients as possible small enough so that they are insignificant and need not be coded for transmission and consequently, discrete transform coding has the potential of reducing redundancy. For the design of proposed technique, we need to not only extract the position information of the wavelet coefficients along with the magnitude information but also calculate the distinct feature parameters of motion vectors [5].

Our generalized procedure of feature extraction is based on DWT. A wavelet decomposition of a function is a decomposition in a special basis of functions, so called wavelets. An important property of wavelet transform is that they preserve the spatial localization of image features [6-7]. The wavelet coefficients are organized into wavelet subtree.

Images are preprocessed in order to extract some interesting features with distinct characteristics. Feature extraction is often the first major operation in many image recognition application. In here, we invoke the idea that taking the DWT as a preprocessor, feature parameters are directly obtained by transformed coefficients matrix. Since the extracting operation computes for each group of pixels a list of its properties, the coefficients matrix guarantees that the output of the DWT have some properties might include its centroid, its area, its circumscribing portion, its orientation, its spatial moments, and so on. The continuous wavelet transform can be defined as

$$CWT_f(a,b)=\frac{1}{\sqrt{a}}\int_R \psi\left(\frac{t-b}{a}\right)f(t)dt \quad \dots (1)$$

where $a\in R^+$, $b\in R$ with $a\neq 0$ and ψ is admissible. and then function $\psi^{a,b}$ are called "wavelets"; the function ψ is sometimes called "mother wavelet". From Eq. (1), we choose $a=a_0^m$ where m∈Z, and the dilation step is fixed. For convenience, we will assume $a_0>1$, and thus we choose $a=a_0^m$ $b=nb_0a_0^m$ where m,n range over Z, and $a_0>1$, $b_0>0$ are fixed; the appropriate choices for a_0, b_0 depend on the wavelet ψ. And so the discretized family of wavelet is given by

$$\begin{aligned}\psi_{m,n}(x) &= a_0^{-m/2}\psi\left(\frac{x-nb_0a_0^m}{a_0^m}\right) \quad \dots\dots\dots\dots (2)\\ &= a_0^{-m/2}\psi(a_0^{-m}x-nb_0)\end{aligned}$$

Finally, discrete wavelet transform can be expressed as Eq.(4). In both case, of course, from Eq. (1) and Eq.(4) we assume that ψ satisfies Eq.(5).

$$DWT_{m,n(f)}=a_0^{-m/2}\int dt\ f(t)\ \psi\ (a_0^{-m}t-nb_0) \quad \dots\dots\dots\dots (3)$$

$$\int dt\ \psi(t)\ =\ 0 \quad \dots\dots\dots\dots (4)$$

Consider a two-channel orthogonal filter bank, the usual wavelet decomposition for 2-D images can be expressed as

$$\begin{aligned}A_{2^{j+1}}f &= \sum_k\sum_l h(2m-k)\,h(2n-l)A_{2^j}f\\ H_{2^{j+1}}f &= \sum_k\sum_l h(2m-k)\,g(2n-l)A_{2^j}f\\ V_{2^{j+1}}f &= \sum_k\sum_l g(2m-k)\,h(2n-l)A_{2^j}f\\ D_{2^{j+1}}f &= \sum_k\sum_l g(2m-k)\,g(2n-l)A_{2^j}f\end{aligned} \quad \dots\dots\dots\dots (5)$$

There exist many different types of wavelet function, all starting from the basic formulas (1),(5). Among these function orthogonal wavelet filter banks have lots of good features -conservation of energy, identical analysis and synthesis- but also some constraints. Two main types of filter bank trees: the full-grown tree and the octave-band tree are commonly used. For the purpose of this research, it is necessary to choose a particular DWT, that is, we selected the Daubechies' family of orthogonal wavelets.

Basic procedure for extracting feature parameters after the performing two level DWT, proceed according to the following scheme.

1: Acquire the 1'st frame from image sequences.
2: Perform the 2-level DWT.
3: Calculate a set of feature parameters using DWT coefficients.
4: Set a reference value of feature parameters result from step 3.
5: Using reference parameter, compare the difference with 2-level based parameters.
6: If the disparity is less than threshold value then perform the 3-level DWT and repeat the step 3 - step 4.
else go to step 1.

The coefficients matrix guarantees that the output of the DWT have some properties might include its centroid, its area, its circumscribing portion, its orientation, its spatial moments, and so on.

III. INFERENCE RULES OF WT COEFFICIENTS.

Object tracking schemes, in general, involve two major stages: 1) a feature extraction stage, and 2) a motion tracking stage. Feature extraction stage is carried out by using DWT coefficients. Some useful coefficients are selected at each successive subband to compute the motion vector between the reference value and the current value. But, unfortunately, due to the variation of back ground, some disparity of motion vectors are occurred between inter-frames. To overcome this problem, we introduce a fuzzy technique into this stage. Fuzzy technique formalize the idea that an object can belong to a class with a continuum of membership grade. It allows us to represent ambiguity or uncertainty about the membership of the object itself in a manner typical of human intuition. In general, classes of moving objects that do not have a clear boundaries. These imprecision is expressed in the possibility that an element does not only belong or not belong to a certain class but intermediate grades of membership are also possible. Consequently, in order to design a fuzzy inference system, a crisp data must be translate into if-then language of fuzzy inference.

In general, fuzzy algorithm can employ relational, compositional or implicational inference method. Fuzzy implication P → Q (P implies Q) is a mechanism for generalized modus pones inference. The implication relation is defined by

$$R(j,k)=\bigcup_{j\,k}\mu(j,k)/(j,k)$$
$$\mu(j,k)=\Phi[\mu_A(j),\mu_B(k)] \qquad j\in X,\quad k\in Y \qquad \text{................ (6)}$$

where linguistic/fuzzy variable X and Y take the values of A and B, respectively, and $\mu(j,k)$ is the membership function of the implication relation. The widely used implication operators, such as Mamdani and Larsen are defined by :

$$\Phi[\mu_A(j),\mu_B(k)]=\mu_A(j)\wedge\mu_B(k)$$
$$\Phi[\mu_A(j),\mu_B(k)]=\mu_A(j)\cdot\mu_B(k) \qquad \text{.......... (7)}$$

In our approach, two operations are performed during motion tracking stage: the fuzzy rule generation operation and the inference operation. Because the size of the inference rule is proportional with the number of various parameters, and so as to generate a optimal inference rule, we mainly concerned on following principles:

. Number of rules.
. Average of antecedents and consequents for each rules.
. Shape of membership function per each input.
. Methods chosen to perform the fuzzification, inference, and defuzzification steps.

Based on these conditions of both inference rule and practical considerations found in the industrial application of automated classification, we devised new algorithm which can be adapted to the change of surroundings. Motion tracking algorithm can be formulated informally as follows [8][9]:

1: preprocessing (feature extraction stage)
- Perform the 2-level DWT.
- Calculate a set of feature parameters using DWT coefficients.
- Set a reference value of feature parameters result from step 3.
- Using reference parameter, compare the difference with 2-level based parameters.
- If the disparity is less than threshold value then perform the 3-level DWT and repeat the step 3 - step 4.
  else go to step 1.

2: while image sequence is not empty repeat step 3 - step 9
    begin
3: Calculate the Max. error DWT coefficients ;
4: if Max. error is larger than TH then goto step 3
    else if do:
    begin.
5: Repeat step 6 - step 9
    begin.

begin.

6: for each value of COE applying MV_n from COE_1 to COE_8 do;

begin

7: Find the defuzzification value

8: Find the certainty factor

9: if certainty factor $> \alpha - cut$ then current vector is equal to reference image else not equal to reference image.

end.

10: Store the number of certainty factor

end.

end.

end.

End of algorithm.

Ⅳ. EXPERIMENTAL RESULTS

Two main steps are involved in our simulation for verifying the proposed approach. The first is a preprocessing, in which we extract the feature parameters of moving vectors result from DWT coefficients. The general architecture of the DWT based inference system for inferencing the motion tracking is composed of two basic functional block as shown in Fig. 1.

Fig. 2 and 3 show a tracking results using the Mamdani and the Larsen operator with respect to the case of intensity variation as well as normal condition. For instance, shown in Fig. 2 is a case of stationary condition with respect to the intensity of illumination Non-stationary condition due to the illumination change is shown in Fig. 3.

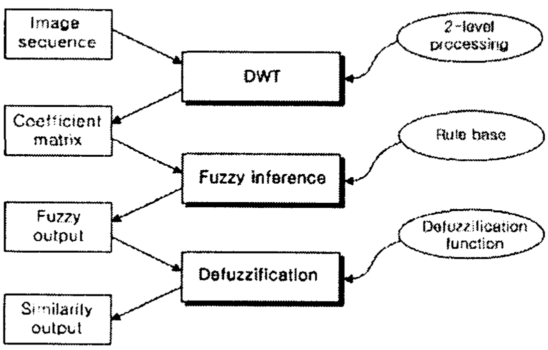

Fig. 1. Block diagram for proposed approach

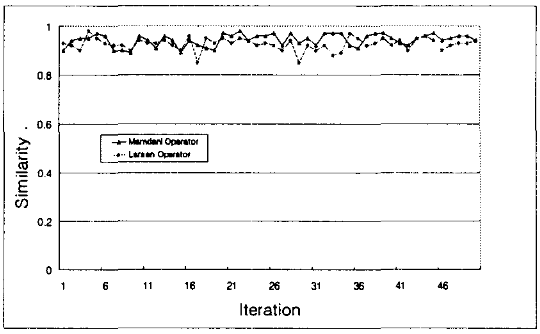

Fig. 2. Degree of similarity (stationary)

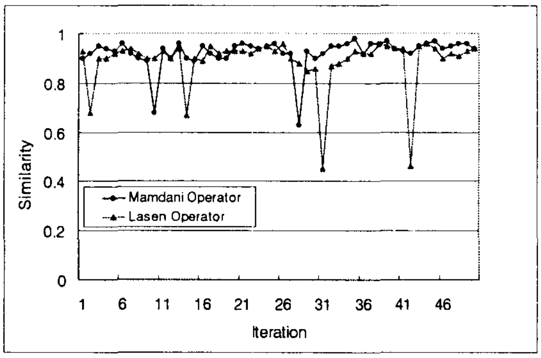

Fig. 3. Degree of similarity(time varying)

In order to find a classification rate, a threshold function or filter, which can be called α -cut is applied to each membership value in the output of similarity. In Fig. 3, it showed that Mamdani operator is superior to that of Larsen's in the similarity.

Ⅴ. CONCLUSION

In this paper, DWT and FI have been applied to our approach to recognize an object pattern. Based on our experimental results and analysis, we draw the following general conclusions:

- 2-level DWT based feature extraction method is proposed, which is relatively simple than space domain method .
- Adaptive fuzzy inference algorithm for automatic identification of moving object is studied.
- The performance has been evaluated with respect the different implication operator.
- Under the same condition, mamdani implication operator is superior to that of Larsen's.

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