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7—5 Image Sequence Retrieval for Forecasting Weather Radar Echo Pattern

Kazuhiro Otsuka,* Tsutomu Horikoshi *
NTT Human Interface Laboratories

Satoshi Suzuki †
NTT Multimedia Business Department

Abstract

A novel framework and method are proposed to retrieve image sequences with the goal of forecasting complex and time-varying natural pattern. As a such pattern, we tackled weather radar images representing the spatial distribution of precipitation, the application is the local short-term forecasting of precipitation. In our approach, the forecast is made by retrieving past patterns similar to the present pattern, and the forecast pattern is produced by using its subsequent pattern of the retrieved sequences. In addition to the global distribution feature and velocity field of the pattern, we extract temporal texture features to catch the features of the echo patterns, which are nonrigid and deformable, and that appear and disappear. Similar sequences are retrieved based on a distance measure between paths in eigenspaces derived from the feature vectors. Several experiments confirm the performance of our retrieval scheme and indicate the predictability of the pattern.

1 Introduction

This world is full of complicated and somewhat vague phenomena. The need for machine vision techniques that are capable of understanding real scenes that contain these phenomena is increasing. As such a target, we decided to tackle weather radar images, which correspond to the spatial distribution of precipitation intensity, and focused on the local short-term(1h-3h) forecasting of precipitation using the radar reflectivity images measured by a weather radar system. Such forecast information is strongly needed for the control of aviation and surface transportation systems, hydrographic networks and so on.

While a numerical forecasting method that is based on a physical model of the atmosphere is being used to produce daily weather reports, the method fails to produce precise short-term forecasts of local precipitation because the physical rules governing the phenomena are only partly understood and the current resolution of the observation is limited. For that reason, current techniques that extrapolate current radar echo patterns with measured velocity, are used for such purpose[1]. However, since the echo patterns included in the radar image, change strongly, the conventional techniques can not produce accurate forecast because they assume the persistency of current phenomena.

In this research, we focus on the repeatability of weather phenomena, that is, precipitation phenomena can be described by a few basic patterns that are governed by rules of pattern sequencing such as pattern A will follow pattern B. This is something that a meteorologist implicitly acquires with experience. Base on this property, we introduce the framework in which the forecast is made by retrieving past patterns similar to the present pattern from a database storing a large set of radar images, and the future patterns of retrieved patterns are used to create the forecast.

The approach of using similar past patterns has the potential in the non-linear prediction of chaotic time series, and has been applied to forecast one dimensional data series such as market activity[2]. A similar concept, founded in inference, is called Memory-based reasoning [3]. However, existing schemes are hampered by the lack of a suitable method of characterizing complex, time-varying,two dimensional patterns.

In our paper, we employ temporal texture features as local features, and a mesh feature of gray level and velocity field as global features. Authors have already developed the feature extraction method of temporal texture features to characterize naturally occurring, non-rigid motion patterns[4][5]. The temporal texture features indicate types of precipitation structures, and the mesh feature represents the spatial distribution of echo patterns as regards global position and pattern shape. The velocity field represents the spatial distribution of atmospheric flow. The mesh feature and the velocity field are transformed into eigenspaces[6][7].

Using extracted features, the pattern at a particular time is represented by a point in the feature spaces. Retrieval of subsequences similar to the key sequences is based on similarity of paths in each feature space.

More studies are using the eigenspace for various appearance-based recognition tasks for man-machine interface and so on. However, the target images were most limited to artificially generated patterns such as human gestures, but naturally occurring patterns. Our research revealed the potential of the eigenspace method in understanding natural worlds and its veiled principles.

This paper is organized as follows. Section 2 introduces the framework and an implementation. Section

*Address: 1-1 Hikarino-oka, Yokosuka, 239-0847 Japan. E-mail: {tsuka@aether, horikosi@nttcvg}.hil.ntt.co.jp

†Address: Urbannet Otemachi Bldg, 2-2-2 Otemachi, Tokyo, 100-0004 Japan. E-mail: tomo@mbd.mbc.ntt.co.jp

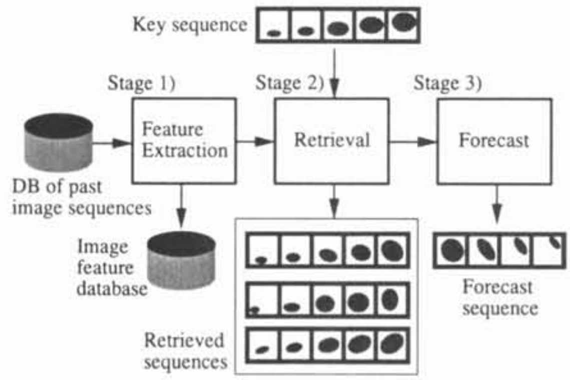

Figure 1: Proposed framework for image sequence retrieval and forecast.

3 shows experimental results. Section 4 draws several conclusions.

2 Framework and Implementation

As shown in Fig.1, the proposed framework consists of three stages: feature extraction, retrieval, and forecast. At first, the sequence of the image features representing characteristics of radar echo patterns are extracted from the image sequence database, which holds a large set of radar images sequentially, and sequences of the feature vectors are stored in the image feature database. Next, the latest image sequence is given as the key sequence, and is compared with each of the stored sequences to retrieve similar sequences. Finally, the subsequent sequences of the retrieved sequences are used to produce forecast information such as the forecasted probability distribution of precipitation. In our system, retrieved and subsequent sequences are also displayed to users, e.g. meteorologists, in order to support their decision making.

2.1 Feature Extraction

Local motion and texture features While the event of precipitation roughly moves along with atmospheric flow, the detail characteristics of the precipitation phenomenon are reflected in the echo patterns, which are nonrigid and deformable, and that appear and disappear continuously. In particular, complex motion and changing texture are important clues in discerning the type of phenomena. To catch the temporal and spatial features of such patterns, we proposed a feature extraction method based on the motion trajectory that is drawn by a moving contour in spatiotemporal space [4][5].

For example, as shown in Fig.2(a), we can extract the motion trajectory included in a local spatiotemporal region as shown as a frame in Fig.3(a). From the motion trajectory, a distribution of normal velocity included in the region can be estimated from the probability distribution of possible tangent planes to the surfaces of the motion trajectory. Fig.2(b) shows the normal velocity

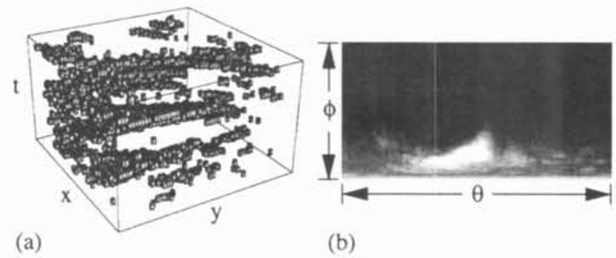

Figure 2: Extraction of temporal texture features. (a)Motion trajectory in local spatiotemporal space, (b)Normal velocity distribution.

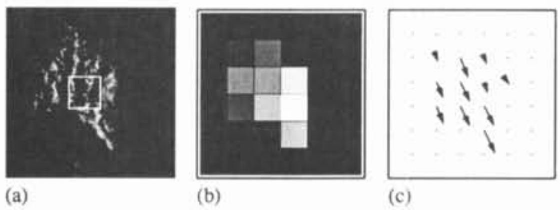

Figure 3: (a)Radar echo image, (b)Mesh feature, (c)Velocity field.

distribution obtained from Fig.2(a). The horizontal axis θ indicates moving direction and vertical axis ϕ corresponds to speed; the gray level of each point indicates the amount of corresponding motion.

From such distributions, we can measure several temporal and spatial features including motion uniformity, which is defined by degree of spreading of the distribution. In this paper, we extract six features $\boldsymbol{x}_1=(f_1, f_2, \cdots, f_6)^t$ including temporal features such as dominant speed f_1, motion uniformity f_2, and occlusion ratio of motion trajectory f_3, and spatial features as directionality of contour placement f_4, coarseness of contour placement f_5, and contrast of motion trajectory f_6. These features identify the characteristics intrinsic to the weather radar echo sequence, such as degree to which echo cells appear and disappear, regularity or uncertainty of motion, and regularity regarding self-organized arrangement of echo cells. Only with these features can the type of radar echo sequence, invariant to position and global shape, be identified.

Global features To catch global features invariant to small changes in texture and position, the mesh feature and the velocity field are calculated. The mesh feature represents a spatial distribution of the echo pattern which represents global position and shape of the pattern. As shown in Fig.3, each image frame at each time step is partitioned into meshes, and average gray level and average velocity of each mesh region are calculated as vector components of the mesh feature and the velocity field, respectively. From a set of the feature vectors, we compute eigenvectors and eigenvalues of their covariance matrix[6][7]. The feature vectors of the mesh feature and the velocity field are then correspondingly transformed

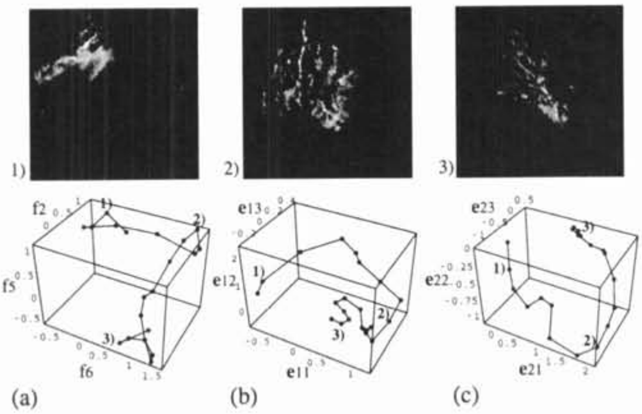

Figure 4: Paths of feature points of (a)Temporal texture [Axes : contrast f_6, motion uniformity f_2, coarseness f_5], (b)Mesh feature in eigenspace, (c)Velocity field in eigenspace. Note each point is 1 hour apart.

into reduced vectors $\boldsymbol{x}_2$ and $\boldsymbol{x}_3$ in eigenspaces that are spanned with eigen vectors with large eigenvalues.

2.2 Retrieval and Forecast

The feature vectors $\boldsymbol{x}_1(t)$,$\boldsymbol{x}_2(t)$, $\boldsymbol{x}_3(t)$, defined above, are calculated at every time step t and be stored the image feature database. The stored feature vectors are normalized regarding variance and mean, and length. Fig.4 shows paths of feature points for a sequence in the feature spaces. Matching the transition in the echo sequence, the feature points move to draw paths in the feature spaces which represent the temporal development of the pattern. Therefore, a similarity between two sequences can be determined from the degree of closeness of the two paths. Here, a dissimilarity measure between two sequences at time i and j is defined as

$$\text{dissimilarity}(i,j) = \sum_{k=1}^{3} \left\{ w_k \sum_{n=0}^{L-1} d_k(i-n, j-n) \right\} \tag{1}$$

where $d_k(i,j)$ is a distance measure between feature points of feature k, L is the length of the parts of the sequences to be compared. The dissimilarity measure is the weighted sum of the distances regarding each feature, where the weights are denoted as w_k in Eq.(1). Euclid distance is used as the distance measure; $d_k(i,j)^2 = (\boldsymbol{x}_k(i) - \boldsymbol{x}_k(j))^t\,(\boldsymbol{x}_k(i) - \boldsymbol{x}_k(j))$.

Also, we set thresholds T_k to distances d_k for each feature vector and retrieve sequences whose distances are less than the thresholds, in ascending order of dissimilarity. Next, forecast information is produced from the subsequent patterns of the retrieved sequences which are also displayed to the users.

3 Experiments

First, we conducted a retrieval experiment to confirm the effectiveness of similar sequence retrieval. First

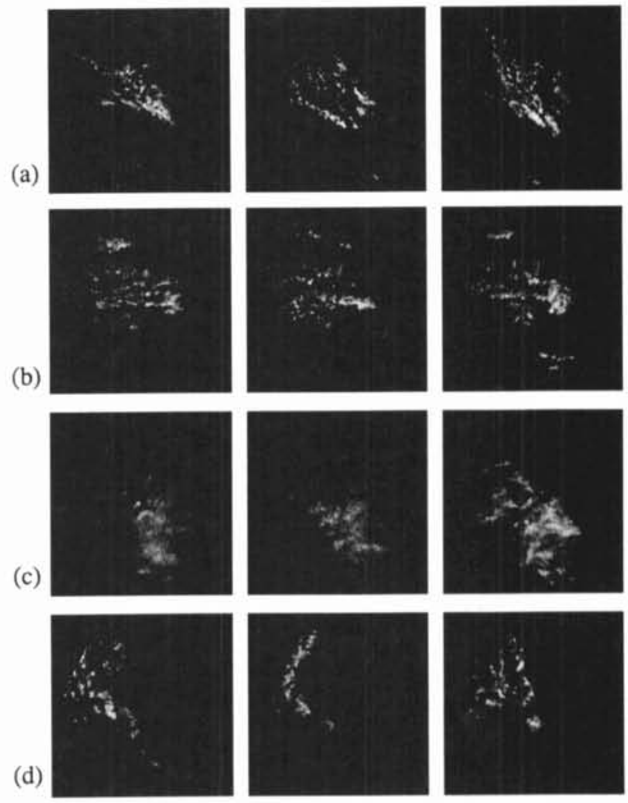

Figure 5: Samples of retrieval for (a)NW-SE Band-shape, (b)W-E Band-shape, (c)SW-NE Stratiform, (d)NW-SE Scattered-type, where (left)Key pattern, (middle and right)Retrieved patterns.

the feature spaces were constructed using approximately 1000 hours of winter-time radar images (12000 image frames) for Sapporo area, Japan. Image size was 340×340 pixels where one pixel corresponds to a 1 km^2 area, and the gray level was 256 levels. Dimensions of the eigenspace of the mesh feature and the velocity field were 5 and 14, respectively. These dimensionalities were chosen to achieve 85% cumulative proportion. From the dataset, parts of sequences including typical echo patterns were manually selected to be classified into one of four classes; A)NW-SE Band-shape, B)W-E Band-shape, C)SW-NE Stratiform, D)NW-SE Scattered-type, based on the judgment of a meteorologist.

As the examples show in Fig.5, A)NW-SE Band-shape pattern forms a set of parallel lines with northwest to southeast orientation, and consists of small echo cells moving with atmospheric flow while repeatedly appearing and disappearing. B) the W-E Band-shape pattern has west to east orientation. C)SW-NE Stratiform pattern is a relatively large diffuse surface that repeatedly appears and disappears quite quickly, while the underlying flow is toward the northeast from the southwest. D)NW-SE Scattered pattern includes echo cells, whose shapes are always changing, and that are scattered at random, moving northwest to southeast. Note: all images in the figures are arranged so that north is at the top. The

Table 1: Hit ratios[%] of retrieved sequences for various feature combinations, where 1:temporal texture, 2:mesh feature, 3:velocity field.

Features	1,2,3	2,3	1	2	3
All Classes	87.5	79.1	68.7	71.1	76.2
Class A)	83.3	76.4	48.8	84.5	68.1
Class B)	72.9	77.0	45.8	58.3	70.8
Class C)	100.0	88.8	93.9	62.5	95.4
Class D)	94.1	79.1	90.2	70.5	68.6

samples totaled 28, 16, 22, and 17 hours for A), B), C), and D) class, respectively.

For each time step within the selected dataset, the dissimilarities to the other data within the selected dataset are calculated to retrieve similar sequences, where $L = 3$, w_1=w_2=w_3=1.0, T_1=T_2=T_3=4.0, and the time step is one hour. Fig.5(middle)(right) shows some examples of retrieved patterns for given key patterns in Fig.5(left). Table 1 shows the average hit ratio of the retrieval. Here, the hit ratio is a portion of candidates determined to be of the same class as the key up to the third rank except the key itself. We can see that all features cooperatively contribute to the high hit ratio. The retrieval error noted was due to intrinsic ambiguity between classes.

Next, Fig.6 shows an example of a forecast. For a given key sequence in Fig.6(a), the first candidate in Fig.6(b) is retrieved from the original 1000 hours dataset. Both sequences include an echo mass moving downward. Fig.6(c),(d) shows actual and forecast images at 1 hours to 3 hours later, respectively. We can see that the global distribution and motion, and temporal development of the forecast pattern are very similar to the actual ones, although the precise texture is different. This experiment confirmed the success of the method in handling strongly changing patterns in contrast to the conventional methods.

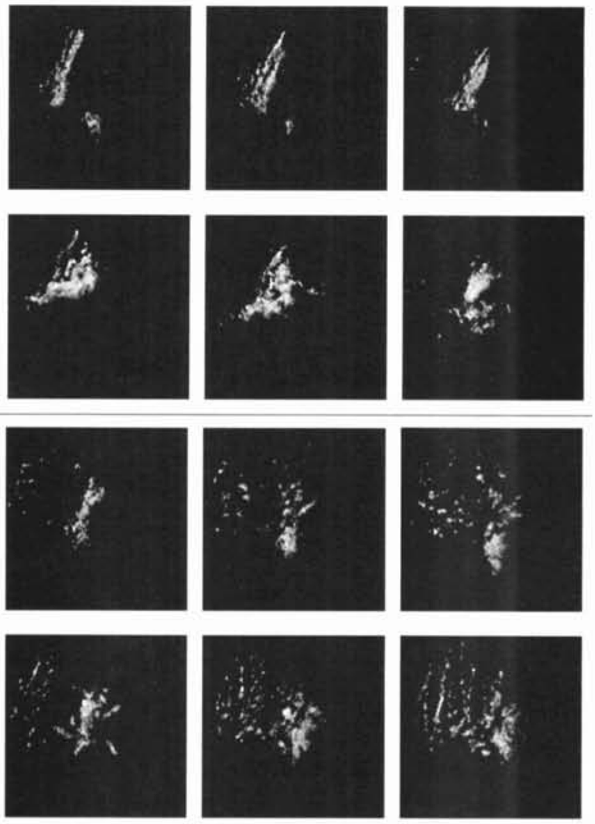

Figure 6: Example of forecast. (a)Key sequence for retrieval, (b)Retrieved sequence, (c)Actual sequence corresponding to forecasted part, (d)Forecast sequence.

4 Conclusion and Discussion

This paper proposed a framework and a method to retrieve similar image sequences toward the forecasting of precipitation. We verified its potential in several retrieve and forecast experiments. Future works include examining the predictability of the framework and synthesizing forecast patterns. Also, there is a need to adaptively refine the weights and thresholds, and to establish links to physical weather phenomena.

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