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Short-Term Rainfall Nowcasting: Using Rainfall Radar Imaging

Peng Wang†[1,2] , Alan Smeaton[1] , Songyang Lao[2], Edel O'Connor[1], Yunxiang Ling[2], Noel O'Connor[1]

[1]CLARITY: Centre for Sensor Web Technologies, Dublin City University, Ireland
[2]School of Information System & Management, National University of Defense Technology, China

Abstract

As one of the most useful sources of quantitative precipitation measurement, rainfall radar analysis can be a very useful focus for research into developing methods for rainfall prediction. Because radar can estimate rainfall distribution over a wide range, it is thus very attractive for weather prediction over a large area. Short lead time rainfall prediction is often needed in meteorological and hydrological applications where accurate prediction of rainfall can help with flood relief, with agriculture and with event planning. A system of short-term rainfall prediction over Ireland using rainfall radar image processing is presented in this paper. As the only input, consecutive rainfall radar images are processed to predict the development of rainfall by means of morphological methods and movement extrapolation. The results of a series of experimental evaluations demonstrate the ability and efficiency of using our rainfall radar imaging in a nowcasting system.

Categories and Subject Descriptors (according to ACM CCS): Image Processing and Computer Vision [I.4.9]: Short-Term Rainfall Prediction by Rainfall Image Processing

1. Introduction

Quantitative precipitation forecast (QPF) is widely used in predicting the distribution of all kinds of precipitation, and is especially valuable in flood forecasting to reduce the effects of weather disasters [RGT*03, FRS02]. Research on quantitative rainfall prediction falls into two main sources, weather radar and numerical weather prediction (NWP). Rainfall radar can capture the real time distribution of precipitation, and it could give fairly good short-term prediction, while the NWP model usually has a longer lead time. Because of the pros and cons both of the two sources have on their own, some research has attempted to combine the two heterogeneous ways in order to explore the advantages of both and has achieved better application in forecasting [IDCX06].

Radar and rain gauges are the most common measurements for collecting rainfall data. Together with rainfall radar, rain gauges are widely used to estimate the areal and spatial distribution of rainfall. Unlike rainfall radar which can estimate rainfall at a high resolution over a large area, rain gauges can only measure rainfall directly at point locations. Because of the advantages that weather radar has, it is employed as an important tool to study a wide range of hydrological applications [CIC04].

As a remote sensing observation, rainfall radar can allow the prediction of short-term forecasts based on the current weather situation, which can provide useful information on rainfall distribution. Rainfall occurrence in a particular area can be studied in order to provide the rainfall rate which can then be used in the future for predicting rainfall levels for similar weather situations. The aim of this paper is to analyse rainfall radar imaging in Ireland in order to predict the short-time rainfall rate in given areas and locations. The overall range of our target area is about 250,000km^2. The longest prediction lead-time of our system is one hour, the grid interval for each prediction is 1.5km, and our prediction is updated at an interval of every 15 minutes.

Section 2 describes related work in rainfall prediction. Section 3 describes problems with using radars to detect rainfall. Subsequently, Sections 4 and 5 describe the rainfall prediction algorithm and systems we employed using radar images. In Section 6, rainfall prediction will be computed

† CLARITY: Centre for Sensor Web Technologies

at 14 different locations around Ireland over varying time periods. The results of the experiment are given and the performances are analyzed and compared. We close the paper with conclusion in Section 7 as well as future work.

2. Related Work

Quantitative rainfall radar prediction is a complex procedure. Because of the numerous climatic variables associated with the microphysics of precipitation systems and for other complex reasons such as observational uncertainties directly caused by radar problems, the prediction of precipitation using rainfall radar can vary to a large extent. Much previous research in meteorology has been carried out to predict the weather using a combination of radar-based observations and weather modeling, whereas our approach is to use radar only.

One area used by QPF is time-series analysis techniques [ETM00], such as Linear stochastic auto-regressive moving-average models (ARMA) [PBLGC93], artificial neural networks (ANN) [RJK98, MNFC92] and K-nearest-neighbour methods (K-NN) [GK93]. In [ETM00], the three methods are compared and more light is shed on the usefulness of ANN and K-NN because they are relatively new as applications in hydrology. Quite distinctly from the ARMA model, ANN belongs to the class of non-linear, data-driven approaches. Due to the complexity of the various aspects of precipitation ANN is employed by training with a set of inputs and outputs to perform prediction without identifying any kind of relationship among the parameters. Without implying any structured interaction, K-NN is a non-parametric regression methodology. It exploits the identification of the nearest neighbors from a large training sample [ETM00].

As a useful model for QPF, mesoscale weather models [JDYRG00, IDCX06] are preferred in the use of numerical weather prediction (NWP). In [IDCX06], a high resolution mesoscale weather model (MM5) is set up to improve the lead time and accuracy for prediction. The weather model takes into account more detailed information such as microphysical data, the relations between weather variables as well as the structure of the atmosphere and its dynamic characteristics. The model has been simulated in a wide range of mesoscale atmospheric processes including precipitation studies [RTBH94, JT97b, JT97a]. However, unfortunately this method seems hard to be able to provide satisfactory forecasts for many hydrologic applications [ETM00, Bra99] and in particular in Ireland where the weather is normally quite unstable because of the influence of the Atlantic ocean.

Although radar detection is affected by problems such as ground occlusion and altitude effects, it could be very useful and efficient in short-term forecasting which is also called nowcasting.

Weather radar data is one of the important remote-sensing information sources providing information on the distribution of precipitation in rainfall prediction [TBTR03, Koj98, CIC04]. Weather radars transmit a pulse of radio waves and detect any rainfall mass through detection of electromagnetic reflection. Thus the weather radars have the potential to estimate the rainfall. A significant advantage has been demonstrated by recent research using weather radar in prediction [GN04]. In [CIC04], the prediction based on weather radar yielded a satisfactory result with the average error rate of 23%. In [PBBV00], the results from radar also proved to be accurate, even more accurate in totaling rainfall than rain gauge models in some cases.

Traditionally, a reflectivity-rainfall (Z-R) relationship is built to produce reliable radar-based predictions of rainfall intensities applying radar reflectivity data in hydrometeorology [GJC99]. The rain intensity R is related to the radar reflection Z according to the power law [Bat73]. The rainfall amounts can be estimated involving the use of reflection via the Z-R relation. This relationship is particularly applied to frontal rainfall prediction.

Heavy rainfall can cause flood disasters, as we know in Ireland, which is why it is important to predict rainfall and run-off discharge in advance. Radar-based nowcasting can make valuable contributions according to hydrological applications, and it could be particularly used for flash flood forecasting/monitoring [IDCX06, PBBV00, MBF00]. As a useful nowcasting tool, rainfall radar readings shows great value in flood prediction. With widely used weather radar networks, the prediction of floods can be provided as severe weather warnings, for water management, air and marine traffic control, etc. The NEXRAD Radar system is a popular Doppler weather radar system which is widely used to track and predict precipitation and atmospheric movement. According to [FJPB98] the NEXRAD system has revolutionized weather forecasting in the United States and has greatly improved the weather service's hydrologic forecasting and warning program. Numerous researchers have been doing research on the prediction of rainfall using weather radar [WFK02, PBBV00, CIC04], including some researchers using numerical weather prediction in addition to rainfall radar [IDCX06, JT00].

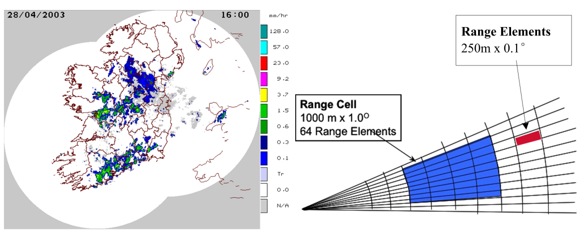
3. Met Éireann Rainfall Radar

Rainfall radar is used to detect the reflection of precipitation. The reflection is related to the size of the raindrops because a larger droplet of rain backscatters more radiation. The radar can provide reflectivity measurements at a sampling rate 5-15 minutes, and with a spatial resolution between 1 and 5 km. With these, we can measure the reflectivity at a height of 3000m–15000m above the surface.

3.1. Met Éireann Radar Service

We have used Met Éireann in Ireland as the meteorological service which uses two rainfall radar stations, at Dublin and Shannon respectively. Figure 1(a) shows the composite of the two radar detections when the images are merged together.

The radars scan every 15 minutes to a range of 240km with a 1km resolution. The rainfall radar image is then converted from reflectivity data in the form of a volume scan which is a sequence of sweeps for increasing antenna elevation angles (see Figure 1(b)). The reflectivity is collected on a polar grid with a resolution of 1km by 1km [WFK02]. Figure 1(b) is a demonstration of the data collection from the Shannon radar. Every range cell contains 64 range elements whose size is 250m by 0.1 degree.



(a) (b)

Figure 1: *Irish radar composite & Radar volume scan.*

3.2. Rainfall Radar Problems

Although rainfall radar images can provide useful information on precipitation patterns, the radar has problems induced by the nature of its own mechanism. Among these problems are the curvature of the earth and ground echoes, which are are the most prominent of the problems.

- **Earth's curvature:** Because the earth is curved, this curvature makes the lowest ground point invisible to radar especially from a far off distance. For example, at a distance of 250km, the lowest point visible to the radar (assuming a flat surface) is 12,000 - 14,000 feet above the surface. The beam will rise above the surface of the earth even though it's emitted horizontally. This means that detection will be weaker at longer ranges and means we can only capture images of the top of clouds at this long distance. The accuracy will also decrease as the range increases and the radar is spread more. Thus the accuracy of radar detection is range-dependent due to the elevation the radar scans, and this will also be reflected by the analysis of our experimental results in Section 6.
- **Ground Clutter:** Ground clutter is formed by the signal reflected by the ground and buildings which is caused by power in the antenna side lobes. It will generally be much worse within 10kms of the radar source. The clutter can result in permanent echoes from mountains or tall buildings. Take Dublin Airport Radar for example, the reflections from from the Mourne mountains in Co. Down and the Galtee mountains yield two main permanent echoes in the radar image which is very evident, even when no rainfall is present (see Figure 2).

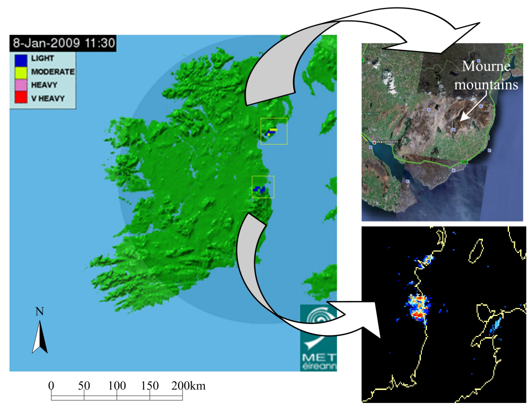


Figure 2: *Topographical explanation for ground clutter at the Dublin Airport Radar.*

The accuracy of prediction is limited due to high dependence on the distance between the detection and radar location as well as the distribution of the drop sizes because of the aforementioned problems rainfall radar has. Errors increase with distance from the radar. Considering the permanent echoes caused by mountains and high buildings, the best signal distance from rainfall radar is at about 75km. In addition, with considerable variations of atmosphere the radar data can't always provide a satisfactory assessment of rain intensities [Krz95]. Heavy rain is usually over-estimated, and light rain is easily under-estimated by rainfall radar reflections.

4. Prediction Model of Rainfall Radar Imaging

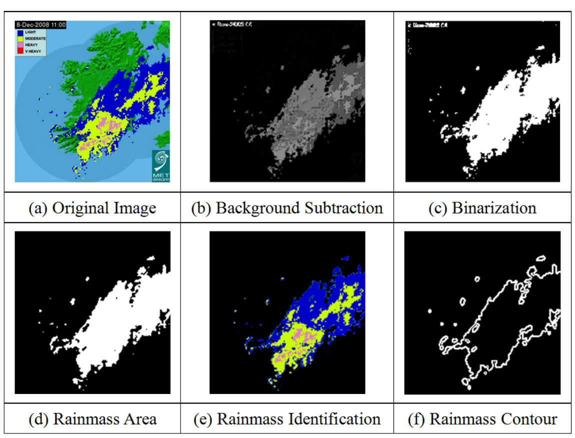
To provide a nowcasting service and find out the effect of rainfall radar problems on short term prediction, we built our prediction model by using rainfall images. Our short-term prediction model consists of rainfall radar image processing, rainfall data extraction and short-term extrapolation, as specified in the following sections.

4.1. Rainfall Radar Image Processing

Rainfall Radar image processing is used to demonstrate rainfall distribution and the current meteorological state at different time nodes to prepare for prediction in the lead-time. The aim of processing is to prepare for data extraction such as gravity identification, velocity and intensity calculation, etc. The results at each of the various end points of processing are stored in a database after being analyzed together with the rainfall radar images. Users will be able to get snapshots of the results and perform queries as well as obtain realtime predictions later via the interface.

To identify the rainmass in each rainfall image, we first selected the non-rainmass background image using color analysis (see Figure 2 left). Taking the newly scraped image from the Met Eireann web page as the source image, the rainmass is analyzed by the following procedures.

- **Background Subtraction:** Going through the background subtraction step, all non-rainmass candidate data are removed from the source image. Only the rainmass areas are left with a black background.
- **Binarization and Non-Interest Reduction:** Binarization is implemented using an empirical threshold. After binarizing the image produced by the last step, we remove small pixel clusters and non-interest regions of the image to help with the identification of pixel clusters corresponding to rain showers. This step combines the use of low-pass filtering and macro-block expanding analysis. All unnecessary regions are removed in this step.
- **Rainmass Identification:** The rainmass can finally be identified as a coloured region, as shown in Figure 3(e). The rainmass contains different levels of rainfall which are used in data extraction, such as the identification of centre of gravity and intensity of rain.
- **Edge Detection:** All image series used in prediction are run through an edge detection algorithm to analyse the overall shape of the rainmass. The outputs of the process are black and white images where white pixels represent the contour of the rainmass (see Figure 3(f)).



(a) Original Image | (b) Background Subtraction | (c) Binarization
(d) Rainmass Area | (e) Rainmass Identification | (f) Rainmass Contour

Figure 3: *Rainfall Radar Image Processing.*

4.2. Rainfall Data Extraction

While one image only contains the static distribution of the rainmass such as the centre of gravity, the rainfall intensity and size at a specified time node, further information can be inferred from a series of consecutive images including rainmass speed, direction and acceleration, etc. All this information, essential for rainfall prediction, is extracted from the various characteristics associated with each rainmass.

We expand the research problem by defining the set of rainmass as $\{R_m\}$, where R_m is the rainmass described by the tuple as follows:

$R_m = \{P_{hy}, M_{or}\}$,

Where P_{hy}, M_{or} stands for physical and morphological characteristics respectively.

4.3. Physical Features

Physical features of each of the rainmass(es) in an image are the attributes of rainmass which correspond to its physical characters. Physical features are defined by $P_{hy} = \{L_{CoG}, V_{el}, D_{ir}, A_{cel}, T\}$,

where

L_{CoG} refers to the location of the rainmass represented by its centre of gravity (CoG) marked with coordinates x and y.

V_{el}, D_{ir}, A_{cel} represents velocity, direction and the acceleration of a rainmass respectively.

T is the time stamp of the rainmass. Because images are processed every 15 minutes, the time stamp is marked in one-quarter regulation.

Among the information related to the physical features of the rainmass, L_{CoG}, V_{el} and D_{ir} are the most frequently used to estimate the distribution of the rainfall cloud in two dimensional domains. L_{CoG} is identified by a weighted average in our approach. V_{el} is calculated using $v = \Delta d/\Delta t$ from physics, where Δd refers to the distance at which the mass has moved based on the rainfall pattern assessment during the time interval Δt which is 15 minutes. Accordingly, $D_{ir} \in [0, 360]$ is denoted by a clockwise angle denoting the direction of V_{el}, where 0, 90, 180, 270 mean "*north*", "*east*", "south" and "west" respectively.

4.4. Morphological Features

In addition to physical features, we represent the morphological features related to the rainmass by defining $M_{or} = \{C_{on}, A_{rea}, I, C_{omp}, C_{lu}\}$

where

$C_{on} \equiv \{(x_i, y_i); 1 \leq i \leq N\}$ is determined by the sequence of edge pixels (see Figue 3(f)).

A_{rea} is the rainmass area evaluated by the expression $A_{rea} = 1/2\sum_{i=1}^{N}(x_{i-1}y_i - x_i y_{i-1})$.

$I \in \{lig, mod, heav, vheav\}$ is a set of rainfall intention levels, where $lig, mod, heavy, vheavy$, represent "light", "moderate", "heavy" and "very heavy" respectively which are indicated by different colours in the original scraped rainfall radar images.

C_{lu} is defined to identify the clustering characteristics of rainmass. It is determined by $C_{lu} = A_{rea}/N_{blob}$, where N_{blob} denotes the number of blobs. It reflects the assembling or diffusing state of each rainmass.

C_{omp} is the compactness of the rainfall mass. We define $\Delta s_i = 1/2(d(v_{i-1}, v_i) + d(v_i, v_{i+1}))$, then C_{omp} is reflected by a rainmass boundary curvature and determined by the form of $C_{omp} = \sum_{i=1}^{N} \Delta s_i / R_c(v_i)^2$, where $R_c(v_i)$ is the radius of the oscillating circle defined by every three consecutive vertices. The normalized C_{omp} reflects the coherence of the whole rainmass, smaller values indicate less compact rainmass which is easy to diffuse in the next series of rainfall radar images.

The characteristics extracted above are specific to each rainmass and allow the rainmass to be uniquely identified in succeeding images over time. Then the rainmass patterns for a specified period can be recognized allowing behavioral comparisons to be drawn between them. The use of a behavioral constant can then be applied to predict the likely rainmass activity in next series of images.

4.5. Rainfall Short-Term Prediction

Rainfall prediction is performed after the rainmass has been identified and the characteristics have been extracted. The model of prediction compares each rainmass with those extracted from preceding radar images. Once the rainmass is identified in preceding ones its activity in the next timeframe can be estimated based on the calculated rainmass behavior pattern. The schematic block diagram for rainfall prediction is given in Figure 4.

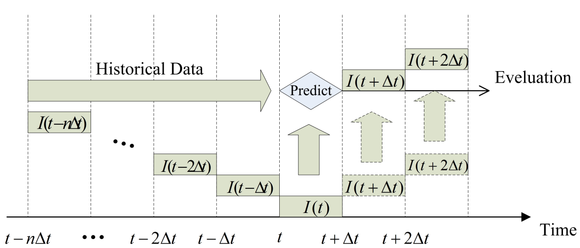


Figure 4: *Rainfall short-term prediction diagram.*

Extrapolation is widely used and gives satisfying prediction especially in very short lead time prediction [KTS00, CLAK05]. Our method of extrapolation is run every 15 minutes after a new rainfall radar image is obtained. According to the speed and direction of rainmasses analyzed from formal consecutive images (e.g. images at t, $t-\Delta t$, $t-2\Delta t$, etc.), the locations of the rainmasses are indicated as a prediction at time $t+\Delta t$, $t+2\Delta t$, etc.

Although the likely error factor will increase while the lead times become longer, the method is more effective when performing short-term prediction for next one or two time windows. Besides, using average smoothing velocity evaluation, the displacement of rainmass the next time does not show as abrupt, especially when rainmasses move in a regular route with respect to speed and direction. In most circumstances the predicted rainmass distribution fits well with the actual one compared with the observed rainfall radar image(see Figure 7). Where there is a shift in speed and/or direction of the rainfall rainmasses these tend to be over several time windows.

The predicted rainfall image is generated to show what the behavior would look like, e.g. current rainmass over Dublin will move in northeasterly direction out to sea at a speed of 40 km/h. As time progresses, the actual rainfall image for that prediction is acquired analyzed and compared with the predicted one, allowing the correction and assessment of the rainfall predicting model. Figure 7 shows an historical series of observed rainfall images and the generated rainfall prediction comparing with the actual rainfall distribution image at the same time.

5. Short-term Rainfall Prediction System

The system we built aggregates rainfall images as input produced from two rainfall radars. To give accurate prediction, the system uses these radar images to monitor the location, movement and intensity of all precipitation. Image processing is implemented in the system to visually track rain clouds in terms of mass, speed direction, etc. and predict rain/no rain for any location.

As Figure 5 shows below, the rainfall prediction system consists of five main components, rainfall image gathering, image processing, data management, rainfall prediction and a touch-sensitive application as the interface to supply users with high-level data visualization.

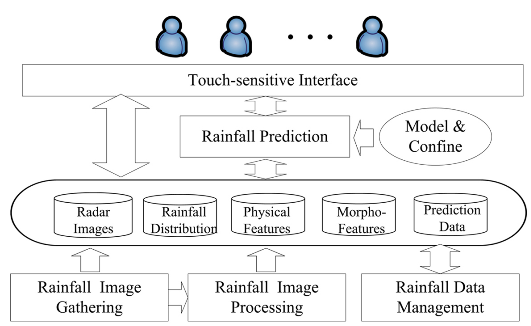


Figure 5: *Short-term rainfall nowcasting system architecture.*

- **Rainfall Image Gathering:** As the only input of the system, rainfall radar images are gathered every 15 minutes. The rainfall image gathering application retrieves the newest radar image tagging it with a time stamp and sends the image to the image processing module before it is stored in the database with the results processed. The prediction can thus be updated every 15 minutes after gathering the new rainfall image data.

- **Rainfall Image Processing:** The rainfall radar images are processed using image processing and morphological methods to mine the data from images, such as the edges of rainmass(es), center of rainfall distribution, rainfall intensity, and the velocity of rainfall development, etc. The data inferred from image processing are stored in the database.
- **Rainfall Data Management:** This is used to manage the rainfall radar images of different periods both the historical and the predicted ones. As the advanced control of the rainfall data, the management application is built to process and manage the various data in the database. Using the application the user can manage sequences of images, view the mapping of rainfall all over the country, and refer to rainfall characteristics and statistics on a specified time segment e.g. the precipitation intensity for a week, month, or a particular year. The locations are added or deleted across Ireland at the user's preference to retrieve the rainfall states at specified locations.
- **Rainfall Prediction:** In terms of rainfall prediction model and limits on prediction, the rainfall prediction is executed using the processed images and associated information gathered into the database. Then the predicted rainfall distribution images and rainfall information are also assimilated in the database.
- **Multi-Touch Rainfall Prediction Interface:** Aiming to exhibit an intuitive representation of rainmass distribution, an interface is implemented on a touch-sensitive interactive table operating a 3D view of the earth (see Figure 6). Multi-touch interface is the software component we developed to apply users' two-handed gestures into human-computer interaction. The movement of precipitation is time-related and is a dynamic procedure depending on spatial representation. Accordingly two-hand collaborative actions are applied to manipulate the earth and a one-hand movement along the axis of time is applied to play forward or backward the rainmass distribution.

With the help of the multi-touch two-handed interaction interface, the information is operated without the salient interference of the keyboard and mouse. That means the gap is well filled between the physical world and information world. The way of interaction on this interface is described in the Figure 6.

5.1. Results and Discussion

The proposed approach and system has been applied to rainfall prediction over Ireland, where 14 different locations are used to predict rainfall likelihood every 15 minutes. About 34,528 predictions have been carried out on every location in our experiments, which means that we implemented about 483,392 predictions in all. Figure 7 shows the difference between the observed rainfall distribution and the predicted one for a 30 minutes lead time. We use recall and precision to denote the accuracy of prediction, which are defined by

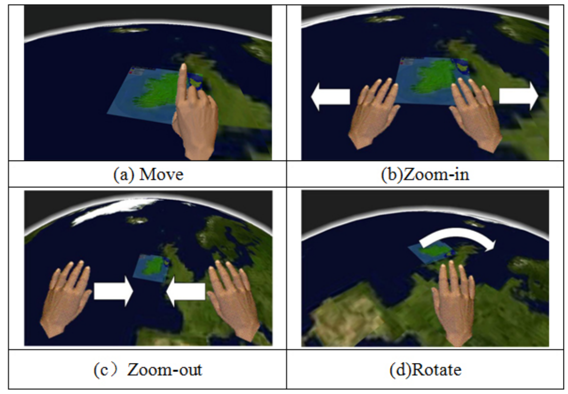


Figure 6: *Bimanual natural action interface.*

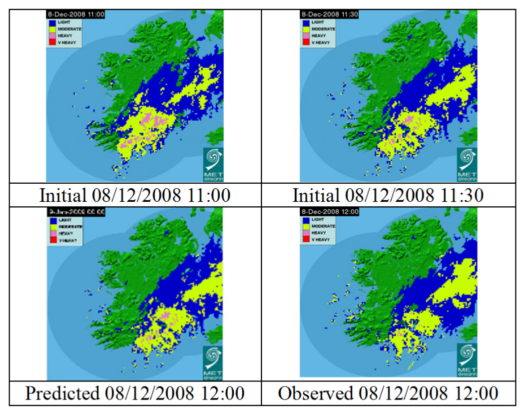


Figure 7: *Rainfall radar nowcasting for half an hour (event: 08/12/2008).*

$$Precision = \frac{R/R}{R/R+R/NR}, Recall = \frac{R/R}{R/R+NR/R}$$

where R/R is the number of predicted rains in a 15 minutes range and where rain actually fell as predicted, R/NR stands for the number of times we predicted rain but it didn't rain, NR/R is the number of predictions of no rain but it rained. The F-Score is calculated using the expression

$$F-Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Prediction results from each location are listed in detail (see Table 1). The rainfall state is estimated over the 14 locations with an overall 0.709 precision. The overall recall and F-Scores are 0.763 and 0.735 respectively.

Table 1: *Experimental results according to locations*

Locations	R/R	NR/R	R/NR	Precision	Recall
Belmullet	647	415	391	0.609	0.623
Birr	2475	1164	679	0.680	0.784
Casement	1908	766	611	0.714	0.757
Claremorris	1416	1333	391	0.515	0.784
Clones	2928	871	848	0.771	0.775
Cork	1797	651	565	0.734	0.761
Dublin	1470	800	405	0.648	0.784
Kilkenny	2345	713	601	0.767	0.796
Malin Head	596	512	164	0.538	0.784
Mullingar	2939	930	748	0.760	0.797
Roches	1861	558	562	0.769	0.768
Rosslare	1330	412	372	0.763	0.781
Shannon	2471	822	1047	0.750	0.702
Valentia	1559	626	627	0.713	0.713
Total	25742	10573	8011	0.709	0.763

From the results we can take the locations with lower F-Score to uncover the effect of distance on the prediction accuracy. Belmullet, Malin Head and Valentia are located on the coast of Ireland and are far from the radars, and they have lowest F-Scores far below 0.70. Kilkenny has the highest accuracy among the 14 locations and it's about 100 km east of the Shannon Airport Radar and 100 km south-west of the Dublin Airport Radar. The same case happens to Mullingar and Rosslare with high accuracy. Because the Dublin and Shannon prediction points are too near to their local radars the accuracy is not very good in prediction (only slightly higher than 0.70) though not as significant as the poor prediction induced by much greater distances. The change of accuracy depending on the distance demonstrates that radar prediction is range-related, the estimation caused by the radar problems introduced earlier.

Table 2: *Experimental results according to time*

Time Period	R/R	R/NR	NR/R	Precision	Recall
00:00-01:59	1713	1152	735	0.598	0.700
02:00-03:59	1570	1568	899	0.500	0.636
04:00-05:59	1870	920	784	0.670	0.705
06:00-07:59	2032	837	740	0.708	0.733
08:00-09:58	2073	719	614	0.742	0.771
10:00-11:59	2326	537	588	0.812	0.798
12:00-13:59	2506	1051	725	0.705	0.776
14:00-15:59	2620	675	729	0.795	0.782
16:00-17:59	2546	709	657	0.782	0.795
18:00-19:59	2322	657	557	0.779	0.807
20:00-21:59	2181	629	473	0.776	0.822
22:00-23:59	1983	1119	510	0.639	0.795

Besides the geographic characters which can affect the accuracy significantly, we also analysed the effect of time related to the experimental result. While the predictions are performed according to the time of day, it can actually be run at any period of a day. Table 2 shows the experimental result accuracy every two hours while the accuracy results every one hour are plotted in Figure 8. The comparison of the performance in different periods shows that the factor of time also affects the accuracy in our system. The best prediction happens between 11:00 and 21:00 which remains at about 0.80. After 23:00 we can see a significant drop until 04:00 at which the poorest performance occurs (see Figure 8), then the accuracy climes until 11:00 in the morning at which the precision and recall are as high as 0.816 and 0.797 respectively.

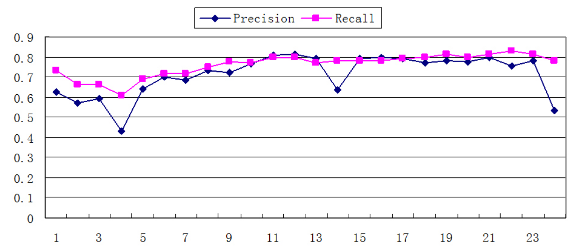


Figure 8: *Comparing in different time periods.*

The experiment shows the ability of rainfall imaging nowcasting system. Based on the above experimental results, we believe that this approach to predicting rainfall has considerable potential. This effectiveness is prominent in the preliminary experiment, especially in particular locations and time periods. In addition, the approach can help to analyze any performance or other problems with the radar system both spatially and temporally. We are currently conducting a more thorough experimental investigation using a lager set of rainfall images including different styles of rain.

6. Conclusion

In this paper, we described a short-term rainfall prediction method which a prediction system is built using rainfall radar images. By image processing and morphologic analysis the rainmasses are identified and related information is extracted, the distribution of precipitation in a given lead time is estimated by an extrapolation algorithm. The effectiveness of the model was demonstrated through a series of experiments.

As the system demonstrates, this algorithm works well in the circumstances of short-term. Because of the inherent problems of rainfall radar, higher accuracy is not achieved because of particular parts in the coverage area of radar and the time of day period. Future work will explore the utilization of microphysics of precipitation which will increase the lead time and the accuracy as well. In our system the radar images are the sole input and the only source of prediction.

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